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INVESTIGATING THE NAVAL LOGISTICS ROLE IN HUMANITARIAN ASSISTANCE ACTIVITIES

by

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March 2015

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According to Department of Defense (DOD) Instruction 2205.02 (June 23, 2014), DOD components must conduct humanitarian and civic assistance (HCA) activities in response to regional conflicts or natural disasters. The Under Secretary of Defense for Policy determines how HCA policy is coordinated and implemented within the DOD and delegates responsibility to the regional combatant commands.

In past modeling efforts for disaster relief, stochastic optimization has been utilized and produced promising results; however, the deterministic nature of optimization models may not fully capture the uncertainty that is inherent in natural disasters and the demand created by them. In order to better understand the effects of the uncertainty surrounding natural disasters and realize a robust logistical response to these events, new approaches are necessary. This thesis develops an asset allocation optimization model for naval logistics, and then uses experimental design techniques to systematically explore solutions to the model. Our analysis reveals the importance of robust planning for natural disaster response to ensure that demand is met and a quick response is possible. Finally, we explore the use of unmanned aerial vehicles as logistics assets, and show that they have the potential to add much benefit to foreign humanitarian assistance.

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INVESTIGATING THE NAVAL LOGISTICS ROLE IN HUMANITARIAN ASSISTANCE ACTIVITIES

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ABSTRACT

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LIST OF ACRONYMS AND ABBREVIATIONS

AA	affected area
AAM	asset allocation optimization model
COCOM	combatant command
COTS	commercial off the shelf
CSV	comma separated value
cu ft	cubic foot
CY12	calendar year 2012
CY13	calendar year 2013
CY15	calendar year 2015
ARES	Aerial Reconfigurable Embedded Systems
DARPA	Defense Advanced Research Projects Agency
DART	Disaster Assistance Response Team
DOD	Department of Defense
DODI	Department of Defense Instruction
DOE	design of experiments
FHA	foreign humanitarian assistance
ft	feet
gal	gallon
GAMS	General Algebraic Modeling System
GB	gigabyte
GHz	gigahertz
GW	gigawatt
HA/DR	humanitarian assistance/disaster relief
HCA	humanitarian and civic assistance
IGO	intergovernmental organizations
kt	knots
lb	pound
NGO	nongovernmental organization
NOB	Nearly Orthogonal, Nearly Balanced
POM	Prepositioning Optimization Model

Q1	quarter 1
Q3	quarter 3
Q4	quarter 4
QR	quick response
UAV	unmanned aerial vehicle
USD (P)	Under Secretary of Defense for Policy
USAID	United States Agency for International Development
VTOL	vertical takeoff and lift
WT	weight

EXECUTIVE SUMMARY

The U.S. military has been involved with disaster response for decades. Few organizations have its capability and capacity, or are as well poised to provide rapid relief during the crucial periods—immediately before and following a disaster. Strategically, the primary benefit to the Department of Defense (DOD) is the potential to develop a positive diplomatic image for U.S. foreign policy. Through humanitarian work, the military can establish itself as not just an organization with great strength and tools for U.S. policy, but also one that is capable of projecting that strength as a soft power and a global force for good.

The DOD is committed to foreign humanitarian assistance (FHA), but planning and conducting FHA efforts is difficult, in large part because of the uncertainty that is inherent in natural disasters and the demand created by them. Likewise, the DOD and, specifically, the U.S. Navy do not currently have a tool with which to conduct robust, quantitative analysis that will assist with planning FHA. While postdisaster data are gathered and studies are conducted, it does not appear that any relevant quantitative modeling takes place. As resources become limited, it is necessary to develop a quantitative method to assess and streamline the disaster relief processes. The resulting analysis can be used to better evaluate risks or better consider alternatives when determining how to effectively use available resources, while still gaining desired results.

Natural disasters are inherently uncertain, and so are the needs for assistance they create. Quantitative approaches to assist in disaster relief processes must recognize this uncertainty. In this thesis, we model and analyze a DOD humanitarian assistance scenario by developing the Asset Allocation Optimization Model (AAM) and conducting experimental design on its parameters. The AAM slightly amends two-stage stochastic optimization models that were previously developed for humanitarian assistance disaster relief (HA/DR) logistics. Relative to those models, we replace warehouses and ground transportation vehicles with naval assets and vertical-lift capability to include unmanned aerial vehicles. The design of experiments (DOE) approach surrounding the optimization model allows the data and assumptions that are made in the model to contain more

uncertainty and variability. This approach allows the analyst to determine the extent to which different sources of uncertainty affect the nature and the quality of the solution, and to seek solutions that are robust to the uncertainty. This is helpful since we cannot always guarantee we will find all the data we need. Most often, the data we must enter into models are estimates made with the assistance of subject matter experts, but they are not perfect.

As we develop the model and conduct experimental design, we gain some insight into the behavior of the model when additional uncertainty is incorporated into various model parameters. The ability to run over 2,500 scenarios in a single design is rather remarkable from a time-saving perspective, and the results reveal insights we might not have made with only a few runs for sensitivity analysis. In many cases, it is not clear what changes to model parameters are required in order to start seeing meaningful differences in the objective value or the solution decisions. Through the application of DOE, we can focus our analysis on the parameters that mean the most to us, but also vary the parameters that we are the least comfortable with in terms of quality. Simultaneously experimenting with a large number of parameters provides more insight than exploring them one at a time.

With each of the designs in this thesis we are able to make new discoveries. First, our study corroborates the findings of other researchers by showing that it is possible to conduct DOE on an optimization model. DOE is no longer only for simulation models or physical experiments.

Second, we demonstrate the importance of ensuring adequate planning and preparation among all the stakeholders and participants in disaster relief. When we run a design with overwhelming demand we note that it is not possible to meet the demand, which shows that measures need to be in place prior to a disaster striking to reduce the expected demand and also to ensure that a quick response following a disaster is possible.

Third, we find that many input combinations can lead to the same AAM optimal objective value. AAM's objective value is calculated as a weighted sum of penalties for unmet commodities and unmet injury transfers. DOE can be used to reveal how

uncertainty in the parameters translates to uncertainty in optimal objective values, identify those parameters with the greatest impact on the optimal objective value, and seek robust solutions.

Fourth, we find that AAM has multiple optimal solutions for many problem instances. The same optimal objective value can result from many combinations of decision variable solutions. Consider, for instance, a monetary budget constraint. We find that optimal solutions given a large budget might involve large expenditures on first-stage decisions, such as prepositioning commodities and expanding ramp space at the affected areas. However, solving AAM with a reduced budget may lead to solutions that provide equally good assistance while spending much less on first-stage decisions. Future work may consider variations of AAM that attempt to minimize cost, perhaps by incorporating cost into the objective function or by using a goal programming approach.

Finally, we explore the implications of UAV use in logistics. These emerging assets have not yet reached their full potential, but through AAM and DOE we can get a glimpse of what the future FHA logistic network might look like and conduct trade-off analysis to determine where we will see benefits or shortcomings. For instance, our experiments indicate that the ability to employ UAVs results in superior solutions relative to complete reliance on manned aircraft. The option for UAVs to deliver commodities lessens the burden placed on manned transportation means and allows for a divide-and-conquer approach to addressing the demand. We conclude that the use of UAVs as logistic assets has the potential to add much benefit to FHA when saving lives and money.

In summary, the motivation for this thesis is a desire to assist logistic planners and help the Navy respond to humanitarian assistance requests in a timely and effective manner. We show there is great potential for quantitative methods to assist in this process—ultimately saving lives, realizing opportunities for cost savings, and increasing goodwill toward the U.S. military.

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I must first thank my very encouraging, supportive, and patient thesis co-advisors, Dr. Susan Sanchez and Dr. Emily Craparo. They both spent their invaluable time and energy in the development of this thesis and me as an operations research analyst. I am so grateful for all they have taught me during my time at the Naval Postgraduate School. I will miss our weekly meetings.

I would not have selected the topic of foreign humanitarian assistance had it not been for Mr. Albert Miller. At his suggestion, I met Dr. Pamela Milligan and Dr. Raymond Buettner. The mentorship I received from them as I shaped my research helped me realize my passion for the themes within this thesis.

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I. INTRODUCTION

According to Department of Defense Instruction (DODI) 2205.02, *Humanitarian and Civic Assistance Activities*, Department of Defense (DOD) components, with host nation approval, shall conduct humanitarian and civic assistance (HCA) activities in response to regional conflicts or natural disasters (DOD, 2014). Title 10 of the United States Code (Humanitarian and Civic Assistance Provided in Conjunction with Military Operations) placed the requirement upon the DOD in 2011 to write HCA policy, which is then transferred to the combatant commanders (COCOMs) to ensure proper coordination and implementation.

Military involvement in worldwide humanitarian assistance in not a historically recent phenomenon; rather, "the earliest recorded instances predate Alexander the Great" (Cuny, 1989, para. 1). The U.S. military has been involved with disaster response for decades. In fact, one of the first observations of the U.S. military providing humanitarian assistance was following World War II, during reconstruction in Europe and Asia (Cuny, 1989).

Few organizations have the capability and capacity of the U.S. military. Moreover, they are not as well poised to provide rapid relief during the crucial periods—immediately before and following a disaster. The military can provide a quick, coordinated reaction to the devastation with its disciplined workforce. From the humanitarian response imperative, the primary capabilities that the military can offer are swift reestablishment of communication, logistic resources, and disciplined manpower; these capabilities can save lives, if quickly deployed (Chiu, Bollettino, Hughey, & Weidie, 2014). In foreign humanitarian assistance (FHA), U.S. military forces are customarily some of the first to arrive, to clear debris and establish security prior to the arrival of humanitarian nongovernmental organizations (NGOs) and intergovernmental organizations (IGOs).

Strategically, the primary benefit to the DOD is the potential to develop a positive diplomatic image for U.S. foreign policy. Through humanitarian work, the military can

establish itself as not just an organization with great strength and tools for U.S. policy, but also one that is capable of projecting that strength as a soft power and a global force for good, helping to “contain some of the negative consequences of major disasters from spreading” (Brattberg, 2013, para. 5). Military assistance is one of the ways that the U.S. government can build partnerships and multilateral security relationships.

According to Burkle, Martone, and Greenough (2014), extreme changes in climate, demographic trends, and urban agglomerations are the factors that increase the frequency of disasters and the complexity of humanitarian emergencies. The increase in frequency creates a necessity for NGOs and IGOs to more closely examine their current procedures and the corresponding impact of their implementation (Burkle et al., 2014). Additionally, the Budget Control Act of 2011 reduced the DOD’s budget by hundreds of billions of dollars, forcing the U.S. military to restructure its priorities. The reduced budget thus increased the need for the DOD to recognize the importance of military planning and preparation in order to provide international humanitarian assistance. Hopefully, such recognition will ensure the U.S. military’s ability to remain compliant with all of its Title 10 requirements.

Currently, the DOD and, specifically, the U.S. Navy do not have a tool with which to conduct robust, quantitative analysis that will assist with planning international humanitarian assistance disaster relief (HA/DR). After HA/DR events, lessons learned and case studies are written. The collected data from these studies identify what was effective and/or highlight areas for improvement, but they are not used to build a new baseline for the next effort. As resources become limited, it is necessary to develop a quantitative tool to assess and streamline disaster relief processes. Therefore, quantitative analysis can be used to evaluate risks or better consider alternatives when determining how to effectively use available resources. This is beneficial to gain the best outcome with the least impact on other needs. The question is not “should the military be involved in humanitarian assistance?” Rather, it is “how can the U.S. military continue to provide assistance in the wake of budget cuts, limited resources, and reprioritization?”

II. LITERATURE REVIEW

A. STOCHASTIC OPTIMIZATION

At the Naval Postgraduate School, there have been a series of published works on two-stage stochastic optimization models. The models were developed to assist with planning for disaster relief. In particular, these works focused on where to preposition assets for disaster relief and further validating the models.

The first of these works is a master's thesis written by Ee Shen Tean (2006). The purpose of Tean's thesis was to consider and optimize the preplacement of relief locations for several types of logistics demands following a disaster—specifically, the need of transportation for people to receive medical care and the need for commodities to sustain those who find themselves displaced in the midst of postdisaster clean up (Tean, 2006). The Prepositioning Optimization Model (POM) that Tean developed considered first-stage decisions for expansion at relief locations, affected areas, and resources. The second-stage decisions were for the logistics network of the problem, with the objective of maximizing the expected number of survivors and the amount of supplies delivered. The POM that Tean developed for his thesis was beneficial because there was no prior known model, so it provided a foundation for similar research.

The following year, 2007, Curtis Heidtke wrote his master's thesis as a review of several alternatives for disaster response. The purpose was to identify the most optimal and valid alternative for determining a planning tool. The belief was that suffering could be limited by ensuring a constant flow of resources (Heidtke, 2007). One of the four approaches Heidtke considered used the POM developed by Tean, with some modifications, to represent two cases for disaster relief (a hurricane and a nuclear explosion) in Washington, D.C. The data Heidtke collected using Tean's POM determined that the POM is an effective tool that can and should be used by planners to reduce the amount of suffering by reducing the resource gap (Heidtke, 2007).

Following the work by Tean and Heidtke, Drs. Javier Salmeron and Aruna Apte published a paper with an updated version of the POM (2010). The primary changes to

the POM included adding an objective, a survival rate, and an additional population type (Salmeron & Apte, 2010). The objectives were, first, to minimize the expected number of casualties due to insufficient commodities and, second, to minimize the inability to transfer people for assistance. The authors also considered different scenarios and performed sensitivity analyses to check for robustness of the model.

Using these previous models as a basis, incorporating similar naming conventions and units of measure, this thesis introduces another slightly different version of a two-stage stochastic optimization model, using Navy and Marine Corps assets as well as unmanned aerial vehicles (UAVs) in the data. The model is explained in Chapter II.

B. DESIGN OF EXPERIMENTS

Design of experiments (DOE) is a method used by analysts to observe and evaluate how a simulation model's input and output behave. While DOE is used for analyzing a simulation model, applying DOE to optimization models is not a widely considered method. Considering that DOE is a way to analyze the behavior and relationship of a simulation model's input and output, there should be an opportunity to use the approach with the input and output of a stochastic optimization model.

Many designs are intended for continuous-valued inputs (factors), and cannot be applied in situations where some of the inputs, such as the number of UAVs, can take on only a limited number of discrete values. Consequently, Vieira, Sanchez, Kienitz, & Belderrain (2011) introduced a design called nearly orthogonal, nearly balanced (NOB). This paper provided a mixed-integer program formulation to build the design to allow for the use of discrete or continuous factors, or both. This versatile design allowed for a previously unavailable mix of factor types in the design. Vieira, Sanchez, Kienitz, and Belderrain (2013) continued their work with mixed-integer programming to extend the factors within a design to discrete, continuous, categorical, or a mix of those types (Vieira et al., 2013). This type of design greatly enhances the analyst's ability to gain significant insight into the complexities of the model they are exploring.

C. UNMANNED VEHICLES IN LOGISTICS

As interest in unmanned vehicles has increased, there has also been an increase in studies exploring if UAVs should be used as a delivery method in military and commercial supply chains. There are numerous benefits to implementing UAVs as logistics tools, such as reduced cost, lower risk, and greater flexibility (McCoy, 2003). Including UAVs as logistics assets for the military could be a solution to the DOD's budgetary challenges and allow for improvements in efficiency and effectiveness. With the intent of exploring the potential of UAVs in military logistics, this thesis includes UAVs as an asset in the model.

In 2013, Amazon announced its plan to use the "octocopter" (see Figure 1) as a delivery method for the products sold on its website (*South China Morning Post*, 2013). The Amazon PrimeAir UAV will be able to deliver packages up to five pounds in weight within a 10-mile radius from designated distribution centers (*South China Morning Post*, 2013). This developing logistics capability has the potential to revolutionize the e-commerce industry by providing customers with the products they order 30 minutes after making a purchase (*South China Morning Post*, 2013). The benefits of this capability have not yet been fully realized, but similar to how email allowed for instant communication, this would allow for the quick delivery of items purchased through the Internet.

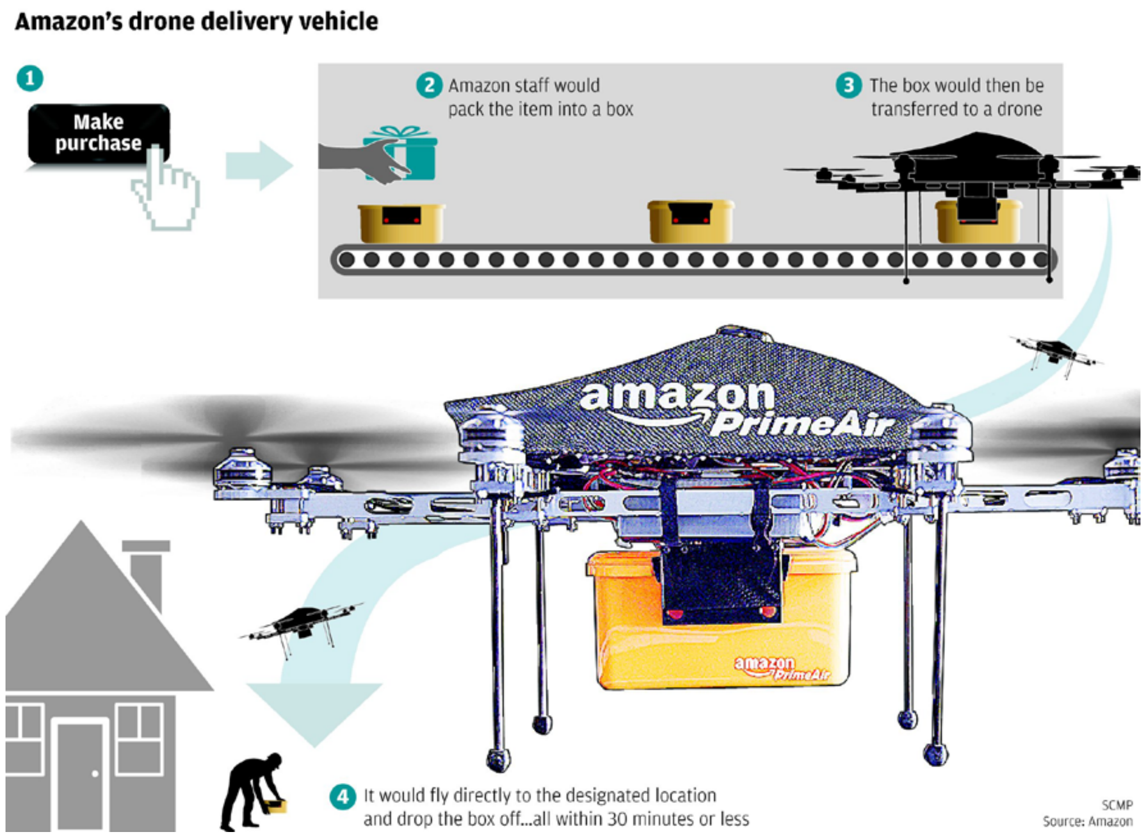


Figure 1. Amazon PrimeAir octocopter concept (from "Amazon Testing 'Octocopter' drones," 2013).

Matternet, a company developing UAV logistic network capabilities, is using drones in several countries to quickly transport lifesaving items. At the request of humanitarian organizations, such as Doctors Without Borders and the World Health Organization, Matternet has tested its drones in Haiti, Papua New Guinea, and Bhutan (see Figure 2) (Leber, 2014). In these countries, conventional transportation infrastructures are underdeveloped, making it difficult to provide necessary supplies and care to people in need (Leber, 2014). The early tests of Matternet's drone appeared successful and could prove crucial to ease human suffering, among many other potentially beneficial logistics purposes. Scan the quick response (QR) code in Figure 3 to view the linked video of Matternet's drone in flight in Haiti.

Figure 2. Matternet drone hovering during testing in Papua New Guinea (from Leber, 2014).

Figure 3. QR code for video of Matternet drone delivering medicine to a clinic in Haiti (from Matternet, 2012).

Of the larger logistic companies, DHL is the first to use UAVs in its operations. It has been researching employed logistics UAVs since 2013. In late 2014, DHL began limited UAV delivery services for an island in Germany. The DHL Paketkopter (see Figure 4) primarily delivers small, time-sensitive packages and medicine to the residents of the island. (DHL Trend Research, 2014) Also in 2014, DHL published a trend report on applications for logistic UAVs. The primary findings of the report are that the two primary uses for business potential, with regard to logistic UAVs, are:

- Urgent express shipments in crowded megacities – improving the delivery speed, network flexibility, and potentially even the environmental record
- Rural deliveries in areas that lack adequate infrastructure (e.g., in Africa) – enabling people in remote locations to be connected to the global trade networks. (DHL Trend Research, 2014, p. 19)

This list of best uses seems to complement the role of disaster relief logistics, quickly transporting commodities and people in locations where there is a lack of adequate infrastructure. To see a video of a paketkopter in flight, scan the QR code provided in Figure 5.

Figure 4. DHL paketkopter (from DHL Trend Research, 2014).

Figure 5. QR code for a video of the DHL paketkopter (from DHL Trend Research, 2014).

Amazon, Matternet, DHL, and even Google (which is conducting tests on their UAV logistic delivery concept in Australia) are optimistic about this concept and are willing to invest in the development of UAVs. In contrast, the U.S. military is still in the early stages of deciding if using UAVs will be beneficial as a logistic asset. In a 2014 study conducted by the National Research Council of the National Academies, it was recommended that the military consider aerial autonomy as a logistic option. The report cited several autonomous vehicle programs conducting research and development of

systems that could potentially solve challenges for sustained logistic operations in complex terrains, areas that do not have the infrastructure for ground transportation, or locations that are dangerous for military members to traverse (National Research Council of the National Academies, 2014). As autonomous vehicle technology develops, there should be more support for the military to adopt the UAV logistic concept.

Based upon current research and the results provided by logistic carriers such as DHL and the e-commerce industry, UAV delivery has only been observed with lighter payloads of five pounds or less. The Defense Advanced Research Projects Agency (DARPA), however, is developing a larger UAV, the Aerial Reconfigurable Embedded Systems (ARES), which can carry up to 3,000 pounds of weight (see Figure 6).

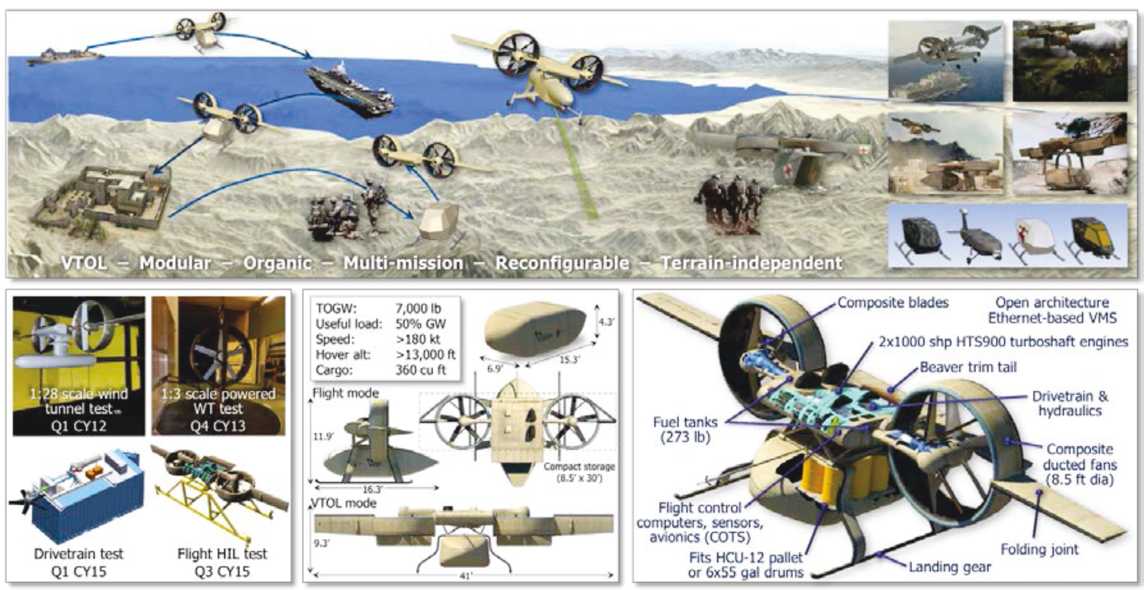


Figure 6. DARPA ARES (after C. VanDercreek, personal communication, April 11, 2014).

The possibility of carrying heavier loads is favorable to the military since its primary resource is its people, and projecting that resource to foreign locations is of paramount importance. A large force requires enough supplies to sustain it and ensure that it can successfully perform its mission. The need for a logistics network and transportation, with the capacity to support more than one person at a time, drives the military to keep searching for transportation means with greater capacity than what has

been offered commercially. A larger UAV, with heavier lift capability, should provide the same capabilities that the smaller commercial UAVs provide, but on a larger scale. Thus, one of the purposes of this thesis is to investigate the impact of the employing larger UAVs in humanitarian assistance logistic efforts. To view the Lockheed Martin Skunk Works video of ARES, scan the QR code in Figure 7.

Figure 7. QR code for video of Lockheed Martin Skunk Works DARPA ARES VTOL simulation (from Lockheed Martin Videos, 2014).

D. CONTRIBUTIONS AND OUTLINE

The contributions of this thesis extend beyond the development and analysis of an optimization model. Specifically, we apply experimental design to a stochastic optimization model. Using DOE, we conduct a robust analysis of the logistic challenges and opportunities that arise when the Navy and Marine Corps are called upon to support HA/DR. The POM developed over the years has proven to be a useful tool for prepositioning assets and attempting to account for uncertainty; however, the output of those models is still deterministic. Natural disasters have many uncertainties associated with them, so a more stochastic approach to developing a disaster-relief-effort planning tool is needed. The methodology used in this thesis permits more variability to be applied to the model. It is hoped that a more well-rounded approach to the HA/DR logistic problem could be effective for the U.S. military, which is often asked to do more with less.

The remaining chapters of this work provide details about the formulation and describe the data, constraints, assumptions, and limitations of the two-stage, stochastic optimization model. Chapter III provides the modified stochastic optimization model. Chapter IV is devoted to a more in-depth discussion of DOE and the methodology applied to the model in Chapter III. Lastly, Chapter V reports the findings of the thesis.

III. MODEL

This chapter introduces the Asset Allocation Optimization Model (AAM) and the experimental designs that were applied to it. The AAM data, variables, and equations are described to allow for an understanding of how the model works, as well as to provide details needed for any future research.

A. ASSET ALLOCATION OPTIMIZATION MODEL

AAM is a linear, mixed-integer, two-stage stochastic model. The first-stage decisions include expansion to various facilities and capabilities in the model. Second-stage decisions include some short-term capability expansions, as well as deployment of assets to scenario-specific affected areas.

Figure 8 shows a schematic diagram of the entities present in AAM, as well as their movement among various locations. Initially a number of naval platforms (surface assets) are conducting routine operations at various locations in the world. Upon learning of a disaster, it is necessary to mobilize these assets to appropriate relief locations near the disaster area. Once on station for assistance efforts, the ships deploy aircraft that carry personnel and commodities to areas affected by the disaster, while removing injured survivors from those areas and transporting them to relief locations for medical attention.

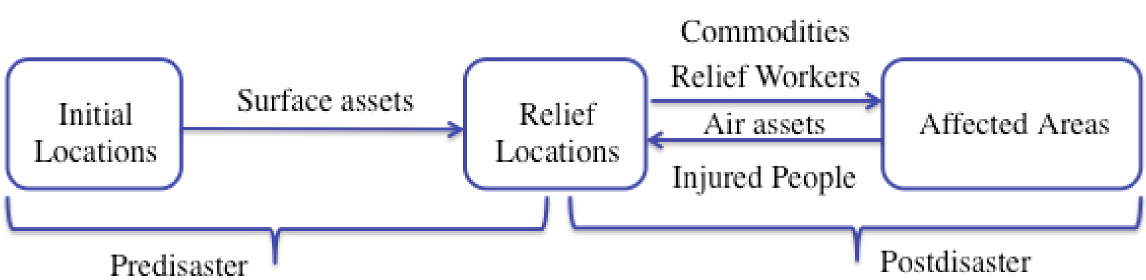


Figure 8. AAM network.

AAM defines a relief locations index that reflects naval ships and land-based relief locations. The ships are considered relief locations once they arrive at their designated positions off the coast and begin the relief mission, thus, the relief location index refers to both a ship and its designated geographic relief location. While a wide range of ships are available in the set, the maximum time parameter restricts ships that are permitted to participate in disaster relief based upon the time it will take the ship to travel from its initial location. Each ship arrives equipped with a number of aircraft, henceforth referred to as transportation means. AAM models two types of transportation means: *general* and *special*. General transportation means are manned aircraft that can carry a mix of people and commodities. Special transportation means are UAVs that can only carry commodities. By including UAVs in the model, we can explore what impact these developing assets could have on naval logistics. Each aircraft departs its relief location carrying commodities or a mix of commodities and relief workers. The manned aircraft return to their relief locations with relief workers and injured survivors in need of medical attention. The aircraft always return to the relief location from which they departed, following an out-and-back pattern. UAV use in logistics is not currently a military capability, so we assume that UAVs only transport commodities, not relief workers or survivors.

AAM's mathematical formulation is:

1. Indices and Index Sets

$i \in I = \{1,2,3,...\}$	Set of origin locations
$j \in J = \{1,2,3,...\}$	Set of relief locations
$a \in A = \{1,2,3,...\}$	Set of affected areas
$t \in T = \{1,2,3,...\}$	Set of transportation means
$T_j^J \subset T$	Subset of transportation means that can depart from or drop off at relief location *j*
$T^R \subset T$	Subset of transportation means that require ramp space
$\omega \in \Omega = \{1,2,3,...\}$	Set of scenarios

2. Parameters and Units

a. Scenario-Dependent Data

$\boldsymbol{dcom_a^{\omega}}$	Commodities needed in affected area *a* under scenario $\boldsymbol{\omega}$ [ft^3 x 1,000]
$\boldsymbol{dsur_a^{\omega}}$	Number of potential survivors in affected area *a* under scenario $\boldsymbol{\omega}$ [survivors]
$\boldsymbol{t_{tja}^{\omega}}$	Time taken for transportation means *t* to travel from relief location *j* to affected area *a* and back under scenario $\boldsymbol{\omega}$ [hours]
$\boldsymbol{wpc^{\omega}}$	Relief workers required to handle commodities at under scenario $\boldsymbol{\omega}$ [workers/ft^3 x 1,000]
$\boldsymbol{p^{\omega}}$	Probability of scenario $\boldsymbol{\omega}$ occurring

dos_j^{ω} Days on station at relief location j under scenario ω [days]

b. Survivor Data

$hpps$ Number of survivors that health personnel can handle [survivors/health personnel]

$ichpps_j$ Initial number of health personnel at relief location j [health personnel]

$mehpps_j$ Maximum expansion for health personnel at relief location j [health personnel]

$vechpps_j$ Variable expansion cost for health personnel at relief location j [$/health personnel]

c. Ramp Space Data

icr_a Initial ramp space capacity at affected area a [ft^3 x 1,000]

mer_a Maximum expansion for ramp space at affected area a [ft^3 x 1,000]

$vecr_a$ Variable expansion cost for ramp space at affected area a [$/ft^3 x 1,000]

d. Commodity Data

icc_j Initial capacity for commodities at relief location j [ft^3 x 1,000]

mec_j Maximum expansion for commodities at relief location j [ft^3 x 1,000]

$vecc_j$ — Variable expansion cost for commodities at relief location j [\$/ft^3 x 1,000]

e. Transportation Means Data

ict_t — Initial number of units of transportation means t available at each relief location [number of units]

met_t — Maximum expansion for transportation means t [number of units]

$vect_t$ — Variable expansion cost for additional unit of transportation means t [\$/unit]

$comcap_t$ — Commodity capacity of transportation means t (if loaded with commodities only) [ft^3 x 1,000/transportation means x trip]

$wcap_t$ — Relief worker capacity of general transportation means t (if loaded with relief workers only) [workers/transportation means x trip]

$scap_t$ — Survivor capacity of “general” transportation means t (if loaded with survivors only) [survivors/transportation means x trip]

h_t — Daily available hours of transportation means t [hours/transportation means]

r_t — Operating range of transportation means t [hours]

f. Miscellaneous Data

ti_j	Time taken for transportation means *t* to travel from origin location to relief location *j* [hours]
mti_j	Maximum allotted time for transportation means *t* to travel from origin location to relief location *j* [hours]
b	Total budget allocated [$]
qc	Relative penalty for unmet commodities (i.e., *qc* displaced people are assumed to perish per thousand cubic feet of unmet commodities) [survivors/ft^3 x 1,000]
horizon	planning horizon [days]

3. Derived Sets and Data

$J^S \subset J$	Subset of relief locations where survivors could be dropped off; derived as $\{j \in J \mid ichpps_j > 0 \text{ or } mehpps_j > 0\}$
$J^C \subset J$	Subset of relief locations from where commodities could be supplied; derived as $\{j \in J \mid icc_j > 0 \text{ or } mec_j > 0\}$
$A^R \subset A$	Subset of affected areas where ramp space exists or may exist; derived as $\{a \in A \mid icr_a > 0 \text{ or } mer_a > 0\}$
$T^G \subset T$	Subset of transportation means used for general missions; derived as $\{t \in T \mid scap_t > 0 \text{ and } wcap_t > 0\}$

$T^S \subset T$	Subset of transportation means used for commodity delivery only; derived as $\{t \in T \mid scap_t = 0$ and $wcap_t = 0\}$
$K \subset T \times J \times A$	Subset of three-tuples (t,j,a) where it is feasible for transportation means t to travel from j to a; derived as $\{(t,j,a) \in T \times J \times A \mid t_{ja} \le r_t, t \in T_j^J$
$K^G \subset K$	Subset of three-tuples $\{(t,j,a) \mid (t,j,a) \in K, t \in T^G, j \in J^C \cup j \in J^S\}$ for general transportation means t transport both commodities and people from j to a and back to j
$K^S \subset K$	Subset of three-tuples $\{(t,j,a) \mid (t,j,a) \in K, t \in T^S, j \in J^C\}$ where it is feasible for special transportation means t travel from j to a and then to j
ics_j	Initial capacity for survivors at relief location j [survivors]; calculated as $ics_j = ichpps_j \times hpps$
dos_j^{ω}	days on station derived as; $dos_j^{\omega} = \left\{ \begin{array}{c} 0, \text{ if } ti_j \ge mti_j \\ \dfrac{horizon \times 24 - ti_j}{24}, \text{ if } < mti_j \end{array} \right\}$
$vecs_j$	Variable expansion cost for survivors at relief location j [\$/survivor]; calculated as $vecs_j = vechpps_j / hpps$

4. Decision Variables and Units

a. *Commodity Decision Variables*

$COMD_{tja}^{\omega}$	Commodities delivered by transportation means *t* travelling from *j* to *a* then *j* under scenario ω [ft^3 x 1,000]
UC_{a}^{ω}	Unmet commodity demand at affected area *a* under scenario ω [ft^3 x 1,000]
EC_{j}	Expansion for commodities at relief location *j* [ft^3 x 1000]

b. *Survivor Decision Variables*

$NSURR_{tja}^{\omega}$	Number of injured survivors transported for medical care from *j* to *a* by transportation means *t* under scenario ω [survivors]
ES_{j}	Expansion needed for injured survivors at relief location *j* [survivors]
UI_{a}^{ω}	Unrescued survivors at affected area *a* under scenario ω [survivors]

c. *Ramp Space Decision Variables*

ER_{a}	Expansion needed for ramp space at affected area *a* [ft^3 x 1,000]

d. *Transportation Means Decision Variables*

ETM_{t}^{ω}	Additional transportation means *t* needed under scenario ω [number of units]
$NTRIP_{tja}^{\omega}$	Number of trips from *j* to *a* by transportation means *t* under scenario ω [trips]

TWD_{ta}^{ω}	Total number of relief workers carried by transportation means *t* to affected area *a* under scenario ω [workers]

5. Mathematical Formulation

a. Objective Function

$$\min \sum_{\omega} p^{\omega} \left(\sum_{a} qcUC_{a}^{\omega} + UI_{a}^{\omega} \right) \tag{1}$$

b. Budget Constraint

Total Budget

$$\sum_{j \in J^S} vecs_j ES_j + \sum_{j \in J^C} vecc_j EC_j + \sum_{a \in A^R} vecr_a ER_a + \sum_{t} vect_t ETM_t^{\omega} \le b \qquad \forall \omega \tag{2}$$

c. Commodity Constraints

Maximum Expansion

$$EC_j \le mec_j \qquad \forall j \in J^C \tag{3}$$

Maximum Supply

$$\sum_{(t,a)|(t,j,a) \in K} COMD_{tja}^{\omega} \le icc_j + EC_j \qquad \forall j \in J^C, \omega \tag{4}$$

Meet Demand

$$\sum_{t \in T^G} \sum_{j|(t,j,a) \in K} COMD_{tja}^{\omega} + UC_a^{\omega} = dcom_a^{\omega} \qquad \forall a, \omega \tag{5}$$

d. Transportations Means Constraints

Maximum Unit Expansion

$$ETM_t^{\omega} \le met_t \qquad \forall t \in T^G \text{or } T^S, \omega \tag{6}$$

Total Hours for General Transportation Means

$$\sum_{a|(t,j,a) \in K^G} t_{tja}^{\omega} \times NTRIP_{tja}^{\omega} \le dos_j^{\omega} \times h_t \times (ict_t + ETM_t^{\omega}) \qquad \forall t \in T^G, j \in dos_j^{\omega} > 0 \tag{7}$$

Total Hours for Special Transportation Means

$$\sum_{a|(t,j,a)\in K^S} t_{tja}^{\omega} \times NTRIP_{tja}^{\omega} \le dos_j^{\omega} \times h_t \times (ict_t + ETM_t^{\omega}) \qquad \forall t \in T^S, j \in dos_j^{\omega} > 0 \tag{8}$$

*e. **Survivor Constraints***

Maximum Expansion

$$ES_j \le mes_j \qquad \forall j \in J^S \tag{9}$$

Maximum Capacity

$$\sum_{(t,a)|(t,j,a)\in K^G} NSURR_{tja}^{\omega} \le ics_j + ES_j \qquad \forall j \in J^S, \omega \tag{10}$$

Unmet Injury Transfers

$$\sum_{t\in T^G} \sum_{j|(t,j,a)\in K^G} NSURR_{tja}^{\omega} + UI_a^{\omega} = dsur_a^{\omega} \qquad \forall a, \omega \tag{11}$$

*f. **Relief Worker and Capacity Constraints***

Relief Workers Accompany Commodities

$$TWD_{ta}^{\omega} \ge wpc^{\omega} \times \sum_{j|(t,j,a)\in K} COMD_{tja}^{\omega} \qquad \forall t \in T^G, a, \omega \tag{12}$$

Capacity of Special Transportation Means

$$COMD_{tja}^{\omega} \le comcap_t \times NTRIP_{tja}^{\omega} \qquad \forall (t,j,a) \in K^S, \omega \tag{13}$$

Joint Capacity of General Transportation Means (Outgoing)

$$(COMD_{tja}^{\omega} / comcap_t) + (COMD_{tja}^{\omega} \times wpc^{\omega}) / wcap_t \le NTRIP_{tja}^{\omega} \qquad \forall (t,j,a) \in K^G, \omega \tag{14}$$

Joint Capacity of General Transportation Means (Incoming)

$$(NSURR_{tja}^{\omega} / scap_t) + (COMD_{tja}^{\omega} \times wpc^{\omega}) / wcap_t \le NTRIP_{tja}^{\omega} \qquad \forall (t,j,a) \in K^G, \omega \tag{15}$$

g. Ramp Space Constraints

Maximum ramp space expansion

$$ER_a \le mer_a \qquad \forall a \in A^R \tag{16}$$

Maximum capacity

$$\sum_{t \in T^R} \sum_{j|(t,j,a) \in K} COMD_{tja}^{\omega} \le icr_a + ER_a \qquad \forall a \in A^R \tag{17}$$

h. Decision Variable Domains

$$COMD_{tja}^{\omega} \ge 0 \qquad \forall t, j, a, \omega \tag{18}$$

$$UC_a^{\omega} \ge 0 \qquad \forall a, \omega \tag{19}$$

$$EC_j \ge 0 \qquad \forall j \tag{20}$$

$$NSURR_{tja}^{\omega} \ge 0 \text{ (integer)} \qquad \forall t, j, a, \omega \tag{21}$$

$$ES_j \ge 0 \text{(integer)} \qquad \forall j \tag{22}$$

$$UC_a^{\omega} \ge 0 \qquad \forall a, \omega \tag{23}$$

$$ER_a \ge 0 \qquad \forall a \tag{24}$$

$$ETM_t^{\omega} \ge 0 \text{ (integer)} \qquad \forall t, \omega \tag{25}$$

$$NTRIP_{tja}^{\omega} \ge 0 \text{ (integer)} \qquad \forall t, j, a, \omega \tag{26}$$

$$TWD_{ta}^{\omega} \ge 0 \text{ (integer)} \qquad \forall t, a, \omega \tag{27}$$

B. MODEL DESCRPTION

The objective function (1) minimizes the expected number of deaths across all scenarios, where deaths are caused by both unmet commodity demand and unmet injury transfers. Equation (2) is the total budget constraint. This ensures the costs of expansion for injury transport, commodities, ramp space, and transportation means remain within the allocated budget. Injury transport expansion at relief locations, commodity expansion at relief locations, and ramp space expansion at affected areas (AAs) are first-stage decision variables, while expansion for transportation means is a second-stage decision variable.

The commodity constraints are Equations (3)–(5). The maximum expansion constraint in Equation (3) prevents the expansion from exceeding the amount of commodities permitted at relief locations. Equation (4) prevents the commodities delivered by transportation means from exceeding the initial capacity for commodities and the expansion permitted. Equation (5) calculates unmet commodity demand.

Equations (6)–(8) pertain to transportation means. Equation (6) enforces the maximum number of additional units allotted in the system. Equations (7) and (8) are the total hours of constraints for general transportation assets and special transportation assets, respectively. The total hours of constraints prevent general and special transportation means from exceeding the available number of operation hours. Although these constraints represent a relaxation of a true scheduling model, they approximately capture time constraints inherent in a disaster relief effort in a computationally efficient manner.

Equations (9)–(11) pertain to survivors. Equation (9) ensures that the expansion for the number of injured survivors dropped off at relief locations does not exceed allowable limits. The maximum capacity constraint in Equation (10) safeguards against the overextension of relief location resources for injury assistance. Equation (11) pertains to the demand for the survivors at the affected areas and calculates the total number of survivors not rescued.

Equations (12)–(15) are relief worker and capacity constraints. Equation (12) ensures that sufficient relief workers are transported on general transportation means to accompany the transported commodities. Once commodities are distributed, the relief workers return with the transportation means to the relief location from which they originated. The total capacity allocated to relief workers, commodities, and survivors on general and special transportation means is constrained by the number of trips undertaken in Equations (13)–(15).

Ramp space constraints are listed as Equations (16) and (17). Equation (16) prevents ramp space expansion from exceeding maximum ramp space for each affected area. Equation (17) ensures that the total commodities delivered to the affected areas remains less than the initial ramp space and ramp space expansion at each AA.

Finally, Equations (18)–(27) define decision variable domains.

C. SITUATION DISCRIPTION AND DATA

We model a situation in which a storm is approaching Bali, Indonesia from the southeast. The storm is expected to devastate three southern coastal regions of the island: Klungkung (area 3), Gianyar (area 2), and Denpasar (area 1). Each of the three regions is impacted with decreasing intensity, respectively, and each region is also an AA. The Indonesian government requested relief assistance and approval was given to the U.S. military to provide assistance. Disaster assistance response teams (DARTs) have also been mobilized; IGO and NGO support is available while U.S. military assistance is provided.

First-stage decisions are made prior to the need for tasking a FHA mission when naval assets are conducting standard maritime operations. The first-stage decisions include expansion for injury transfers, commodities, and ramp space. Second-stage decisions (e.g., commodities delivered, unmet demand, number of injury transfers, rescue workers transferred, transportation expansion, and number of trips) are made after the disaster takes place and scenario and affected area data, shown in Table 1, impact the model. The scenario data in Table 1 shows five scenarios that were developed, $\omega_1 - \omega_5$. Scenario ω_1 is the storm affecting all three areas severely. In scenario ω_2, areas a_2 and

a_3 are affected moderately. Scenario ω_3 has the storm affecting a_2 and a_3 severely. In scenario ω_4, the storm is severely affecting a_1 and moderately affecting a_2 and a_3. For the final scenario, ω_5, the areas are not affected and there is no demand for assistance for the transport of people or commodities.

Table 1. Scenario and affected area data for base case.

Scenario	Probability of Scenario Occurring	Injuries			Commodity Demand		
		a_1	a_2	a_3	a_1	a_2	a_3
ω_1	0.60	16	51	403	0.51	1.70	13.5
ω_2	0.15	0	26	202	0	0.87	6.8
ω_3	0.10	0	102	807	0	3.40	27.2
ω_4	0.05	16	26	202	0.51	0.87	6.8
ω_5	0.10	0	0	0	0	0	0

The demand data in Table 1 was estimated by applying a factor to the population of those regions of Bali. According to the United States Agency for International Development (USAID) Typhoon Haiyan factsheet (2014), approximately 38 percent of U.S. humanitarian funding was attributed to the DOD, or $34.5 million out of $90.8 million. The population totals for the three regions of Bali were compared to the ratio of people affected in the three most impacted regions of the Philippines after Typhoon Haiyan. The estimated number of people impacted in Bali by a similar natural disaster was multiplied by 38 percent to determine the proportion of people that the DOD response would need to assist. The commodity demand data was determined by using the estimated value of commodities needed per person calculated in Curtis Heidtke's 2007 thesis.

Table 2 shows the following relief location data: initial capacity of health care personnel, maximum expansion for health care personnel, variable expansion cost for health care personnel, initial capacity for commodities, maximum expansion for commodities, variable expansion cost for commodities, initial capacity for injured survivors, maximum expansion for injured survivors, and variable expansion cost for injured survivors. Some of the data was derived from the data provided in Ee Shen Tean's thesis (2006) and Curtis Heidtke's thesis (2007).

Table 2. Relief location data for base case.

Relief Location	***ichpps***	***mehpps***	***vechpps***	***icc***	***mec***	***vecc***	***ics***	***mes***	***vecs***
CVN	4	10	1,500	34	10	100,000	20	50	300
CG	1	0	1,500	4.08	0.5	100,000	5	0	300
LHD	4	10	1,500	35.36	10	100,000	20	30	300
LPD	4	6	1,500	5.44	0.7	100,000	20	30	300
DDG	1	0	1,500	2.42	0.5	100,000	5	0	300
LCS	1	0	1,500	2.42	0.5	100,000	5	0	300
Bali 1	25	20	1,500	100	0.5	100,000	125	100	300
Bali 2	40	15	1,500	100	0.5	100,000	200	75	300
Bali 3	15	15	1,500	100	0.5	100,000	75	75	300

The transportation data found in Table 3 includes the initial number of aircraft, maximum expansion for aircraft, commodity capacity, worker capacity, survivor capacity, daily available hours, and operating range of each transportation means. In order to determine the data in Table 3, we used the same approach and calculations as Curtis Heidtke (2007). The variable expansion cost is the reimbursable hourly rate times 100 block hours, divided by cargo capacity. The reimbursable rates were taken from the fiscal year 2014 DOD reimbursable rates memorandum (Roth, n.d.).

Table 3. Transportation means data for the base case (after globalsecurity.org, n.d.; C. VanDercreek, personal communication, April 11, 2014; E. Nabasny, personal communication, February 20, 2015).

Aircraft	***ict***	***met***	***vect***	***comcap***	***wcap***	***scap***	***h***	***r***
MV-22	6	4	1876589.99	0.74	24	12	24	10
CH-53	4	8	962857.14	1.75	55	24	24	8
UH-1	3	6	1709657.32	0.32	14	6	24	8
C-2	1	2	996744.19	0.86	26	12	24	8
SH-60	12	24	2234366.43	0.28	5	5	24	8
ARES	16	4	526580.56	0.36	0	0	24	24
MQ-8	4	2	6320166.67	0.03	0	0	24	10

D. ASSUMPTIONS

The overarching assumption with the model is that the storm has an impact similar to that of Typhoon Haiyan in the Philippines. The three AAs were selected based upon geographic similarities to the three most affected areas in the Philippines (“Typhoon Haiyan,” n.d.). The population (“Bali,” n.d.) impact and demand data were scaled with the same ratio. It was also assumed that the DOD would provide the same amount of support that was provided following Haiyan. NGOs and IGOs are also providing support to share the workload. The $30 million budget is comparable to the budget that was spent by the DOD for the Typhoon Haiyan FHA (United States Agency for International Development [USAID], 2014).

We focus on modeling only the emergent phase of the relief effort and assume that ships given tasking to respond to the disaster are within a 120-hour radius from Bali, assuming a travel speed of 20 knots. The time horizon for the relief effort from DOD assets is nine days, with assets providing support as soon as they arrive on station. The manned aircraft receive waivers to allow aircrews to operate for the maximum allowable time and the ARES UAV is permitted to remain in operation for 24 hours, with skilled

operators taking shifts. It was also assumed that no maintenance or downtime is required for the transportation means.

E. BASE CASE RESULTS

The computations were executed on a MacBook Pro, 3 GHz Intel Core i7-4578U processor with 8 GB. The MacBook Pro was partitioned to also contain a Windows 7, 64-bit operating system. The computations were run in the Windows 7 operating system using the General Algebraic Modeling System (GAMS), version 24.3.2 with the CPLEX solver. The model solved in about 4 seconds with approximately 3,700 constraints and 2,900 decision variables, approximately 1,000 of which were integer.

Figure 9 shows the optimal use of transportation means for commodity delivery as a mix of the MQ-8 UAV, ARES UAV, and manned helicopter UH-1 for the base case. In scenario ω_3, when the demand for commodities is the highest, UH-1s conduct deliveries along with the UAVs. From this, it appears that the preference is to utilize unmanned aircraft first and then supplement with manned aircraft, as required. Across all scenarios and for all affected areas, MQ-8 UAVs deliver 13.5 ft^3 x 1,000 of the commodities, ARES UAVs deliver 21.47 ft^3 x 1,000 of the commodities, and 27.2 ft^3 x 1,000 of the commodities were delivered by UH-1 manned aircraft. All commodity demands are met; however, the objective function, Z = $\min \sum_{\omega} p^{\omega}(\sum_{a} qcUC_a^{\omega} + UI_a^{\omega})$, is a minimization of the weighted expected unmet commodities and unmet injury transfers so an objective value, Z = 13.4, indicates that not all injury transfer demands are met. In scenario ω_3, 134 people in need of medical attention were not moved to relief locations from affected areas two and three.

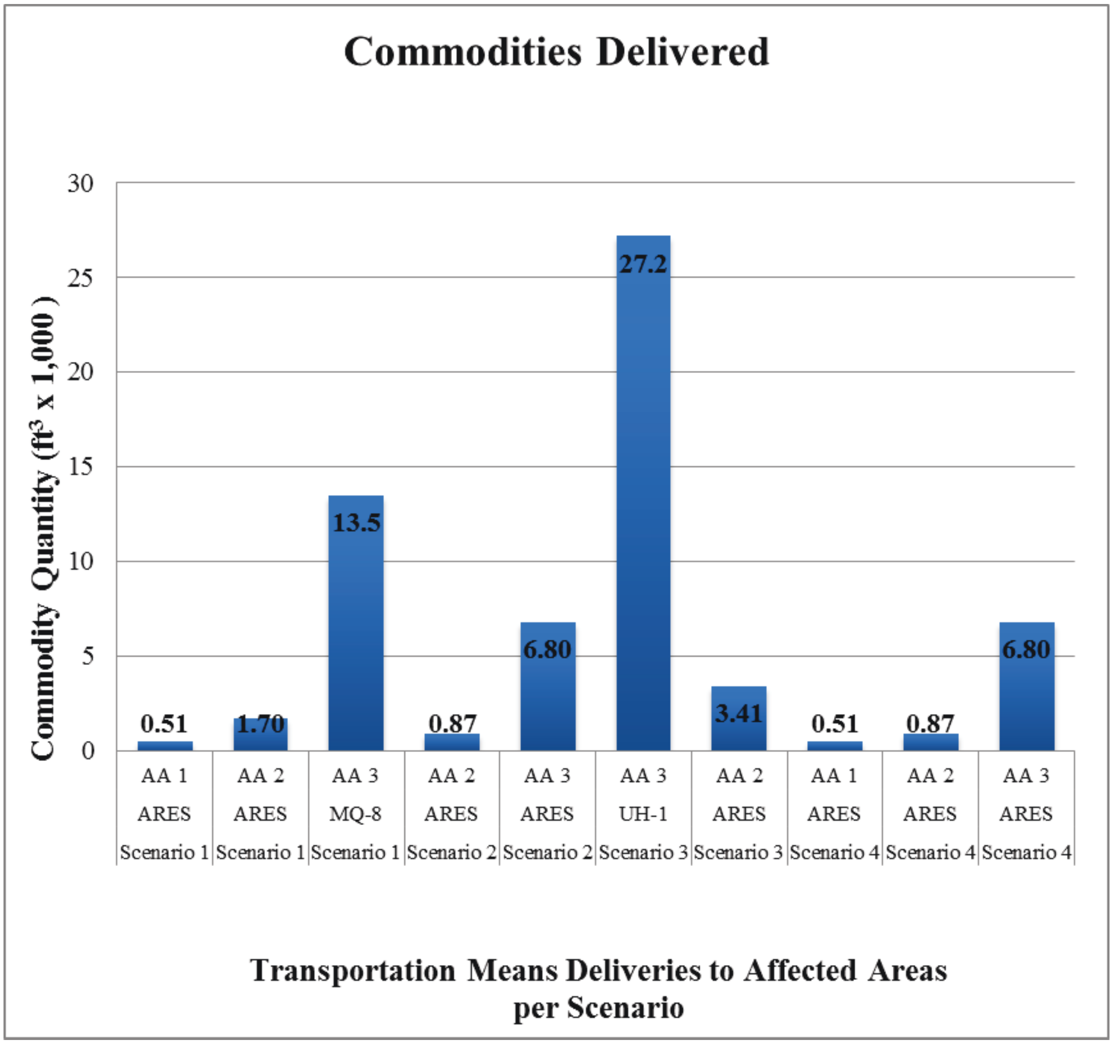


Figure 9. Commodities delivered by transportation means to affected areas.

Similarly, Figure 10 displays the optimal usage of transportation means, but for the transportation of injured people from affected areas. While the UAVs transport the majority of commodities, several manned aircraft (the MV-22, CH-53, SH-60, and UH-1) are available to transport injured people from affected areas to relief locations.

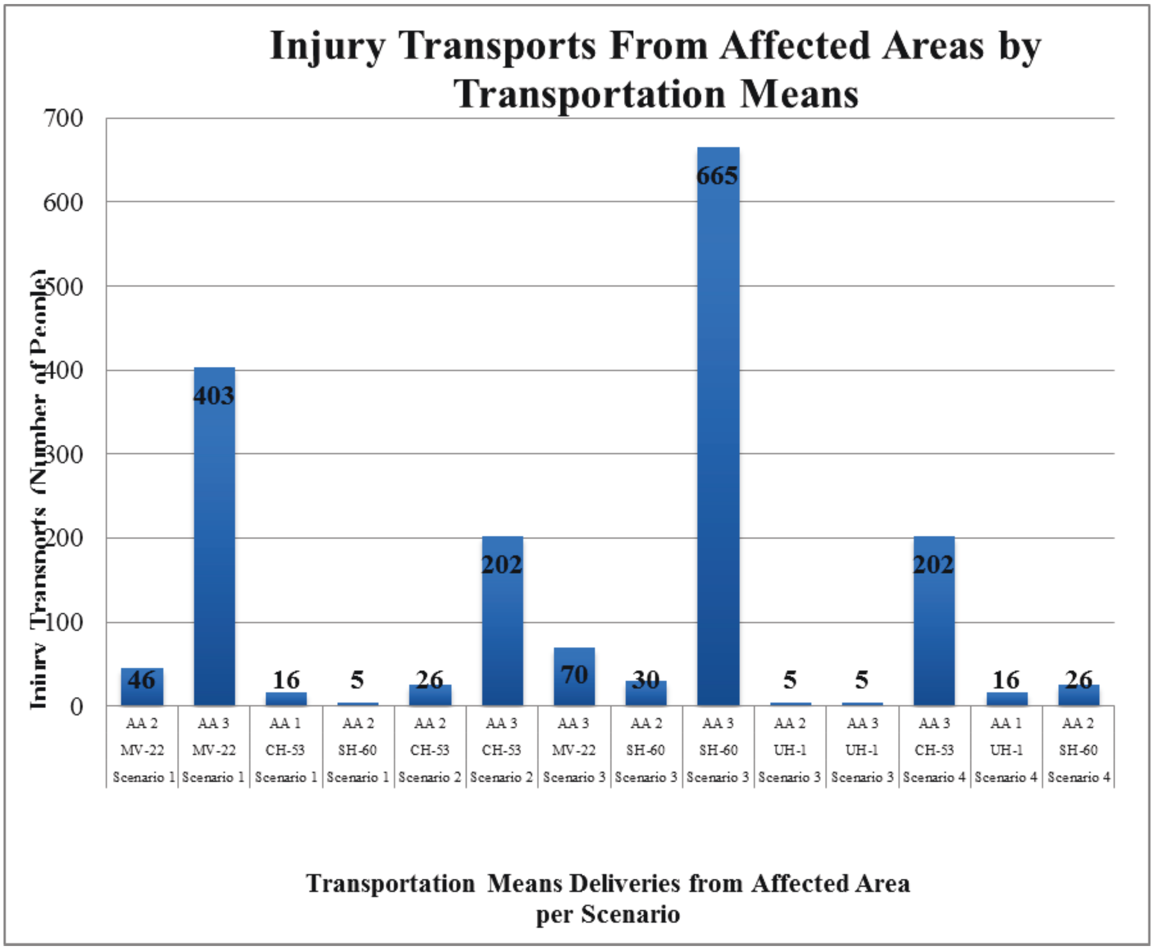
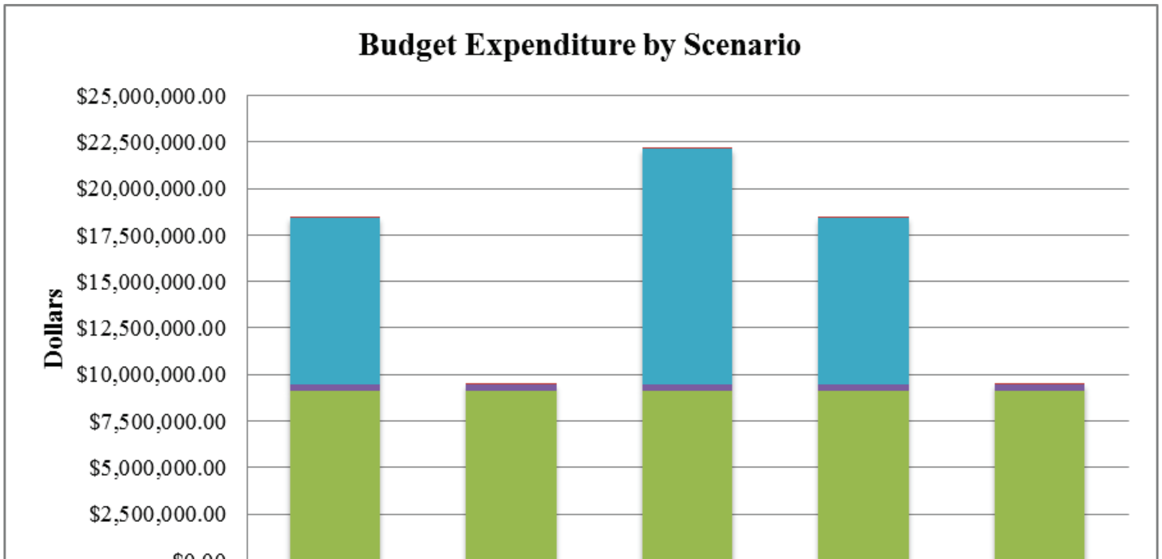


Figure 10. Number of injury transports by transportation means.

Additionally, Figure 11 shows the cost per scenario. All scenarios require expansion for commodities, health care for injured people, and ramp space. Scenarios ω_1, ω_3, and ω_4 also require expansion for transportation means. Additional SH-60s are needed in ω_1 and ω_4 to transport survivors, while scenario ω_3 requires additional UAVs to deliver commodities. In scenario ω_5 the storm does not make landfall so there is no need for commodity delivery or injury transportation so the only expenditures on the budget are those for first-stage decisions for money spent in anticipation of demand.



	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Medical	$90,000.00	$90,000.00	$90,000.00	$90,000.00	$90,000.00
Transportation	$8,937,465.72	$0.00	$12,640,333.34	$8,937,465.72	$0.00
Ramp Space	$360,000.00	$360,000.00	$360,000.00	$360,000.00	$360,000.00
Commodities	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00

Figure 11. Budget expenditure to meet demand in each scenario.

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IV. DESIGN OF EXPERIMENTS ON THE STOCHASTIC OPTIMIZATION MODEL

Typically, DOE is applied to simulation models to gain additional analytical insights. Using statistical theory, it is possible to observe the relationships between input parameters and output measures. From DOE, an analyst is able to identify how the factors affect the response or how the factors interact with each other, which is one of the ways to identify the complexities of the system (MacCalman, 2013). Other complexities that can be identified through DOE "include a factor's diminishing or increasing rate of change, or a threshold that groups output results into vastly different areas" (MacCalman, 2013, p. xvii). Identifying a system's complexities allows analysts to gain a better understanding of how sensitive the system is to the factors. This can then be used to develop an approximate relationship between the input and output of the simulation model, also known as a metamodel.

With DOE, one of the primary keys is to apply the right design type to a model. That decision is very important, since it impacts the types of metamodels that can be developed as a result of data farming (Lucas et al., 2015). Using a metamodel, one can closely calculate the response of the original model based on the range considered when developing the design.

A. METHODOLOGY

A NOB design for discrete and categorical factors (Vieira et al., 2013) was selected to vary the discrete and continuous input data parameters of AAM. Initially, three data tables were selected: scenario probabilities, demand for transport of injured people, and demand for commodities. The first two experiments were run for 512 design points on 15 factors. The third design had 512 design points and 27 factors. Because AAM is a deterministic model, we introduce more uncertainty into specific parameters that are varied in the designs. The final design was similar to the third design with 27 factors, but with slightly different input data. Table 4 shows a comparison of the parameters and factors that were varied with each experiment.

Table 4. DOE comparison.

Parameters	Design 1	Design 2	Design 3	Final Design
Scenario Probabilities (5 factors for 5 parameters)	Varied from AAM base case.	Same as Design 1.	Same as Design 1.	Same as Design 1.
Commodity Demand (5 factors for 15 parameters)	Varied substantially from AAM base case.	Varied up and down from AAM base case.	Same as Design 2.	Varied for an increase of 10 times the levels of Design 2 for a storm with intensity between Design 1 and Design 2.
Injury Transport Demand (5 factors for 15 parameters)	Varied slightly from AAM base case.	Varied up and down 10% from AAM base case.	Same as Design 2.	Varied slightly from Design 2 for a storm between Design 1 and Design 2.
Air Asset Transport Time (2 factors for 1725 parameters)	No variation from AAM base case.	No variation from AAM base case.	Variation included multiplier for travel time and random half-width adjustment for loading variance.	Same as Design 3.
Ramp Space (3 factors for a total of 6 parameters)	No variation from AAM base case.	No variation from AAM base case.	Variation on expansion and expansion cost.	Same as Design 3.
Air Asset Data (7 factors for a total of 14 parameters)	No variation from AAM base case.	No variation from AAM base case.	Variation on initial number of units available and the units available for expansion.	Two variants from Design 3: without UAV expansion and with UAV expansion.

The first design has a large range with respect to the affected areas' demand for injury transport and commodities. The second design varies the upper and lower limits on the injury transfer factors by only 10 percent from the base case. The third design expands on the second design by including 15 additional factors, which vary values in three more GAMS data tables.

The primary difference between the third and final design is that we explore two cases of UAV expansion, the possibility of allowing UAVs to participate in FHA or not. This is to examine the difference between the solutions for current naval logistics practice of not including UAVs, and observe if the solution changes when we introduce UAVs in the logistics network for identical scenarios. We also alter the demand slightly from Design 3 for a storm that could have up to ten times the intensity, and change the budget to conduct experiments with $30 million, $10 million, and no budget.

For all designs, the factors are varied with the spreadsheet named "NOB_Mixed_512DP_template_v1.xlsx: Template for a 300 Factor, 512 Design Point Nearly Orthogonal Nearly Balanced Mixed Design," which was developed by Hélcio Vieira in 2012 to accompany the papers on the topic (Vieira et al., 2011; Vieira et al., 2013). For a detailed diagram of the levels for each of the designs see Appendix A.

Once a design is created, there is a multistep process to grow the data for analysis. First, the cells in the design spreadsheet are copied into a comma separated value (CSV) file. Each of the 512 rows of the CSV file is a design point and a separate AAM problem instance. Second, a Ruby script (see Appendix B) is run from the command line; it pulls the values from the CSV file row by row and constructs 512 new GAMS files, one for each design point. Third, to automate the process of running all the GAMS files, a Windows batch file (BAT) is used to call on GAMS to solve each version of the model. The BAT file creates a new directory for each run to hold 13 CSV output files. Fourth, each type of CSV output file also has a corresponding BAT file to pull that specific CSV output into another folder labeled with that CSV name. Fifth, the 512 instances of that CSV data file are then concatenated into one CSV file. Finally, the data for each type of

CSV file are concatenated and the header duplicates are stripped. The end result is a dataset that is suitably configured for further analysis, with the design points correctly represented by row. This process is repeated for each design.

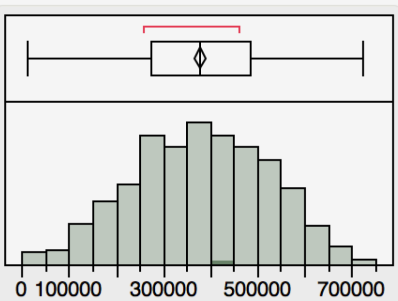
B. ANALYSIS

For each design we investigate the optimal objective value and the unmet demands. We also perform analysis on how the budget is spent as way of looking at expenditures due to first- or second-stage decisions. We attempt to identify if there are differences between the optimal solutions obtained for different designs.

1. Design 1: Overwhelming Demand

The first design represents a case with overwhelming demand for transporting commodities and moderate demand for transporting injured survivors. The mean optimal objective value for the 512 design points of this design is 378,259.69. Figure 12 provides the summary statistics for the distribution. The available assets are not capable of meeting the amount of demand from the population across every scenario, as indicated, with a minimum optimal objective value of 12,328.7. This is almost 1,000 times greater than what was observed in the base case.

Z



Quantiles

100.0%	maximum	725189
99.5%		706321
97.5%		637042
90.0%		565952
75.0%	quartile	482651
50.0%	median	377373
25.0%	quartile	274261
10.0%		190053
2.5%		103723
0.5%		29802
0.0%	minimum	12328.7

Summary Statistics

Mean	378259.69
Std Dev	142068.98
Std Err Mean	6278.6214
Upper 95% Mean	390594.78
Lower 95% Mean	365924.6
N	512

Figure 12. Distribution for optimal objective values of Design 1.

Looking at the unmet commodities and unmet injury decision variables, we can quickly identify the shortfalls noticed in the optimal objective values. Figure 13 shows the positive correlation between commodity demand and the unmet commodity values. Figure 13 only shows this relationship for affected area 1; however, the strong positive correlation was observed for all affected areas.

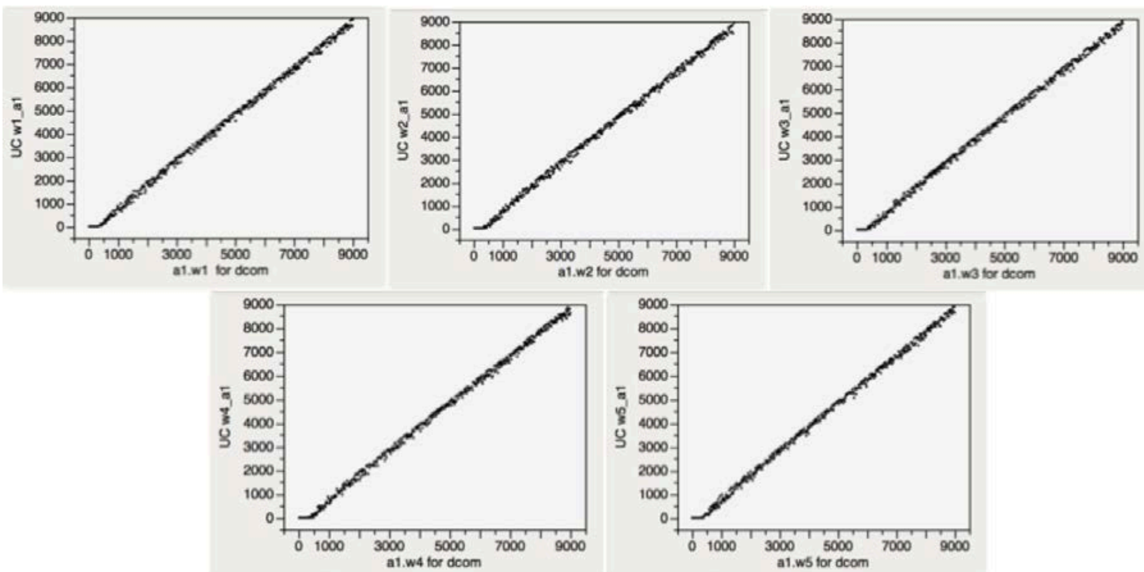
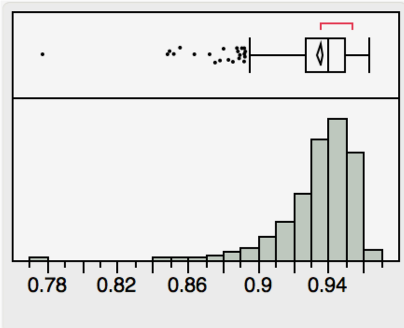


Figure 13. Unmet commodities by demand for commodities at affected area 1.

Figure 14 shows the distribution for the proportion of unmet commodities to commodity demand across all AAs. The histogram displays that the proportion does not go below 0.75. The distribution of the total proportion of total unmet commodities to total commodity demand in Figure 14 shows a negative skew, with a minimum proportion of 0.78.



Quantiles

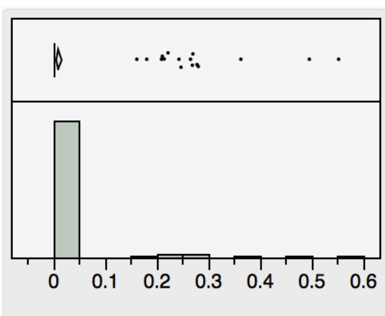
100.0%	maximum	0.96339
99.5%		0.96261
97.5%		0.95885
90.0%		0.95429
75.0%	quartile	0.94882
50.0%	median	0.93934
25.0%	quartile	0.92697
10.0%		0.91035
2.5%		0.88613
0.5%		0.84937
0.0%	minimum	0.77763

Summary Statistics

Mean	0.9351107
Std Dev	0.0201045
Std Err Mean	0.0008885
Upper 95% Mean	0.9368563
Lower 95% Mean	0.9333652
N	512

Figure 14. Distribution of the proportion of total unmet commodities to total commodity demand across all affected areas.

Conversely, there were very few instances when the proportion of total unmet injury transports to total transfer demand was not zero. This is seen in Figure 15. Thus, we conclude that the large optimal objective values in Design 1 are primarily caused by unmet commodities rather than unmet injury transfers.



Quantiles

100.0%	maximum	0.55303
99.5%		0.42138
97.5%		0.21207
90.0%		0
75.0%	quartile	0
50.0%	median	0
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	0.0087342
Std Dev	0.0520203
Std Err Mean	0.002299
Upper 95% Mean	0.0132508
Lower 95% Mean	0.0042175
N	512

Figure 15. Distribution of unmet injury transfers to demand for injury transfer.

Figure 16 shows a partition tree developed using JMP software, Version 10. The optimal objective values are the response. The first split separates the entire group of objective values into two sets in the way that improves R^2 the most, by determining the factor and level that creates the best split. This process continues. With every split in the tree a prediction is made for the objective value with the included data. For this tree, the potential splitting variables included are the probabilities of the scenarios occurring, the demand input values, and the number of trips per aircraft. The leaves to the left indicate

cases associated with lower predicted objective values, while the leaves to the right correspond to cases with higher objective values. The insight gained from this partition tree is that the lowest objective value is achieved as the demand for commodities decreases, probability of scenario ω_5 remains above 0.4, the probability of scenario ω_3 remains below 0.05, and CH-53's take at least 770 trips. The differences are striking. For example, further information from the farthest left leaf (circled in Figure 16) shows that if less than 770 trips are made with CH-53 the average objective value is 102,097.56, while if 770 or more trips are made with the CH-53 the average objective value is 35,650.166. The next lowest mean objective value, 101,360.52, is found to the right of the circled leaves. The R^2 for this tree is 0.847, after 24 splits, signifying how close the predicted values are to the relationships identified in the data; the model can explain 84.7 percent of the variability around the mean. From this tree we can get a sense of which aircraft are considered the most beneficial to the 2,560 possible scenarios within the 512 design points in Design 1.

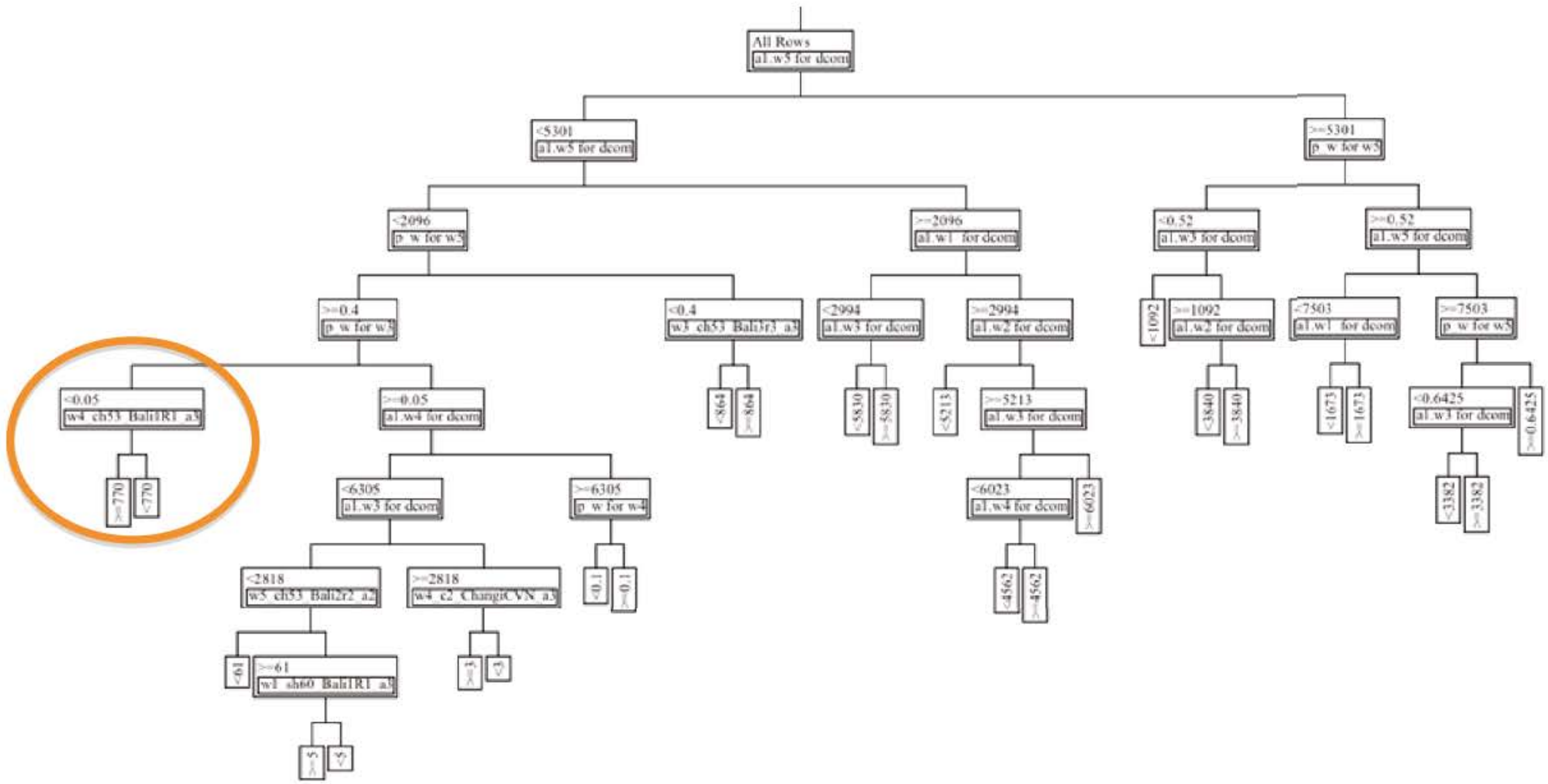


Figure 16. Partition tree of optimal objective value by Design 1 input factors and number of trips per aircraft.

Design 1 results in large optimal objective values due to the inability to meet commodity demand, but it is better to see this with a DOE, rather than experiencing it following an actual natural disaster. When the demand exceeds levels traditionally observed, the standard quantity of assets is not enough to effectively provide assistance. In addition to considering the use of UAVs, coordination and planning among the military, IGOs, and NGOs prior to a natural disaster is even more important. In a case similar to Design 1, opportunities to reduce demand through steps taken in anticipation of the magnitude of a disaster, or ensuring the availability of enough resources, would ultimately decrease unmet demand and save more lives.

2. Design 2: 10 Percent Increase and 10 Percent Decrease of Demand Levels

Similar to Design 1, 15 factors from three tables are varied. The probabilities associated with the types of scenarios are the same as Design 1, but the injury transport demand value ranges are only slightly varied by an increase and decrease of 10 percent from the base case and commodity demand values are also not as large. The optimal values for this design are very good; for every design point, the optimal objective value is zero.

Since all demand is met, we next attempt to identify the percentage of the budget spent to ensure successful relief efforts. Across all scenarios, the average amount spent to provide relief was $15.06 million, which is approximately half of the assigned budget. Recall that this budget is for expansion purposes, and does not include the costs of initial naval resources. Figure 17 provides the summary statistics for the budget spent and shows that the maximum budget expenditure was $29.60 million. So, although the objective values are all identical, the decision variables are not. We begin to consider the possibility of multiple optimal solutions and recognize while there is no incentive to spend less money, this opens up the possibility to consider a decrease in budget.

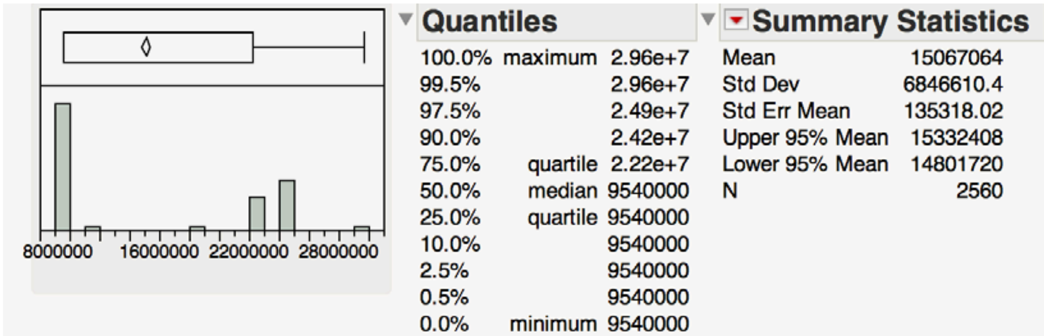


Figure 17. Distribution and summary statistics of budget spent.

With some additional analysis, we determined that the primary budget difference among each design point is with the expansion on transportation means, a second-stage decision. Figure 18 shows the relationship between the budget spent and transportation means expenditure, and Figure 19 shows the transportation means expense distribution and summary statistics.

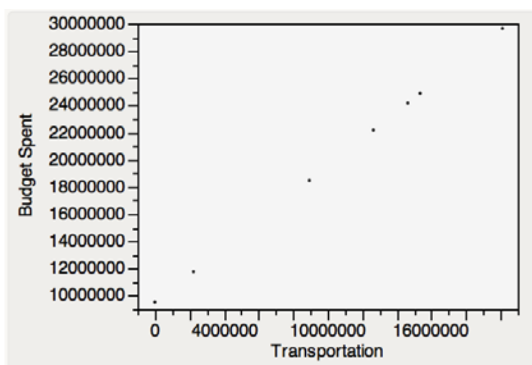


Figure 18. Relationship between budget spent and transportation expenditure.

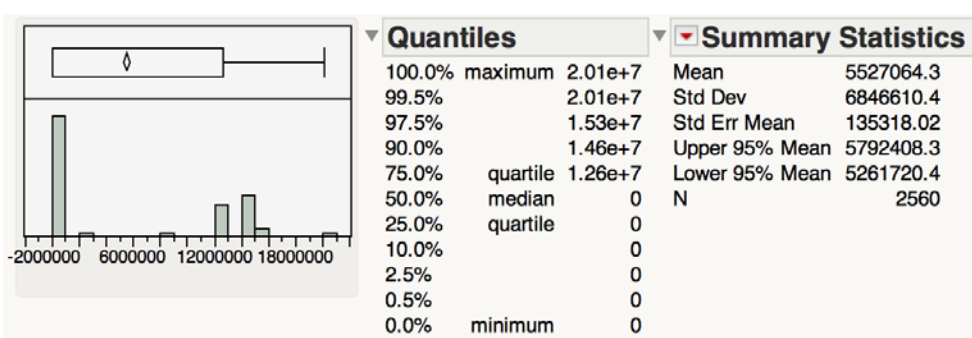


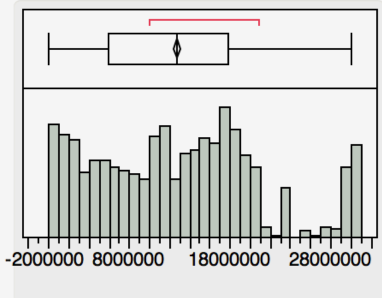
Figure 19. Distribution of transportation expenditure.

For Design 2, the drivers for budget and meeting demand are with transportation means, there is very little variability with any of the first-stage decisions. The proper mix of transportation is necessary to keep the optimal solution values low.

3. Design 3: 27 Factor Design

In addition to the original 15 factors in the previous two designs, 12 additional factors are selected for this design. The times for transportation means to travel between relief locations are varied to explore the impact of uncertainty with respect to travel time and loading and unloading time for passengers and commodities. Applying a multiplier and adding a half-width value to the times in the base case data table allowed for this uncertainty. The multiplier varied the travel time between locations, while uniform random numbers drawn from [-half width, +half width] accounted for the variability in loading and unloading times. Ramp space data are also varied for initial ramp space capacity, amount available for expansion, and cost for expansion. This design also varies the transportation means data, specifically the initial number of units available, and the number of units available for expansion.

Similarly to Design 2, the optimal objective value does not indicate any unmet demand for injury transfers or commodities at affected areas. This design also demonstrates better solutions than the base case, fully minimizing unmet demand to zero. The budget expended, however, was not the same and it seems to contain a little more variability across all scenarios. Although the model is not trying to save money, it is still important to note that in some scenarios part of the budget remains available. In Figure 21, the mean budget spent for Design 3 is shown as $12.7 million, with a maximum spent as the full budget of $30 million. These values are not too different from Design 2.



Quantiles

100.0%	maximum	3e+7
99.5%		3e+7
97.5%		3e+7
90.0%		2.37e+7
75.0%	quartile	1.78e+7
50.0%	median	1.26e+7
25.0%	quartile	5830271
10.0%		1859500
2.5%		458156
0.5%		43295.9
0.0%	minimum	0

Summary Statistics

Mean	12702305
Std Dev	8181351.8
Std Err Mean	161698.16
Upper 95% Mean	13019378
Lower 95% Mean	12385233
N	2560

Figure 20. Distribution of the budget spent for Design 3.

For Design 3, not just the second-stage decision of expansion for transportation means impacted the budget. Additionally, first-stage decisions (medical, commodities, and ramp space) attributed to the variance found in the budget spent. This is likely due to the additional variability applied to the design since the only differences between Design 2 and Design 3 were the additional factors. There is also the possibility for multiple optimal solutions since the objective is to minimize unmet demand and not budget spent. Figure 21 shows the distributions for all of the contributors to the budget variance and, while there was variance with the budget, it did not seem to impact the capability to meet demand and impact the optimal solution value. Without running experimental design on AAM we might not have seen that the introduction of uncertainty to additional parameters would impact both first- and second-stage decisions, but still result in the same optimal objective value. Additional experimental designs are necessary to continue to investigate the reason for why this is occurring, and determine if similar behavior is displayed when the objective value is greater than zero.

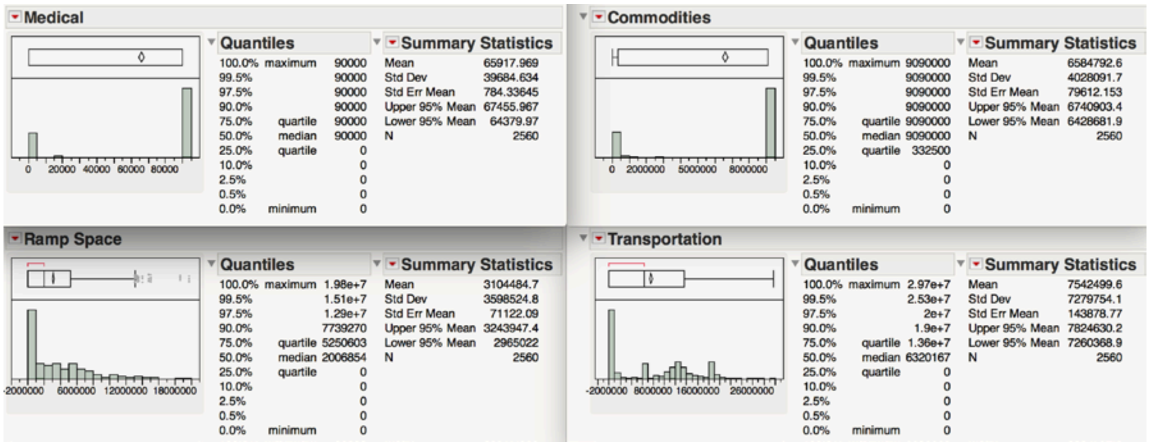


Figure 21. Distributions of budget expenditures for Design 3.

Figures 22–24 show a comparison of distributions for the number of trips transportation means make in Designs 2 and 3. There are some differences among asset usage; as the number of parameters varied increases, some aircraft are used more than others.

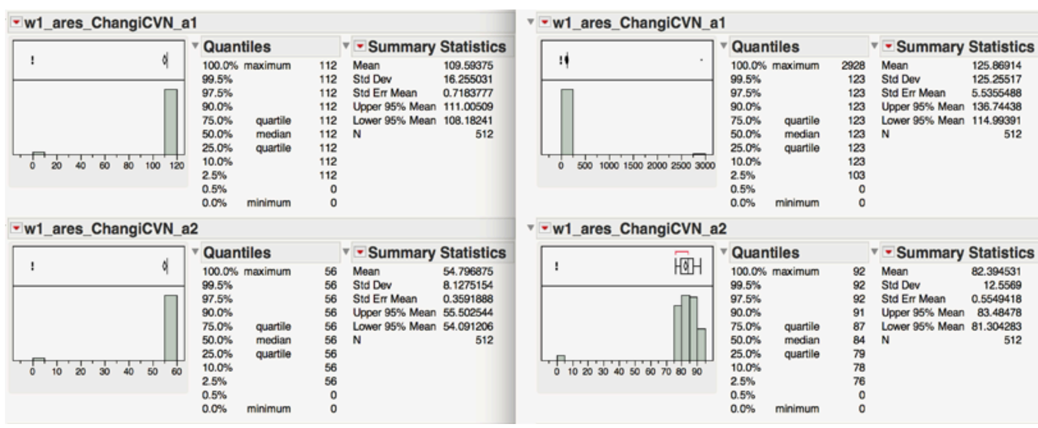


Figure 22. Distribution comparison of ARES usage for Design 2 (left) versus Design 3 (right).

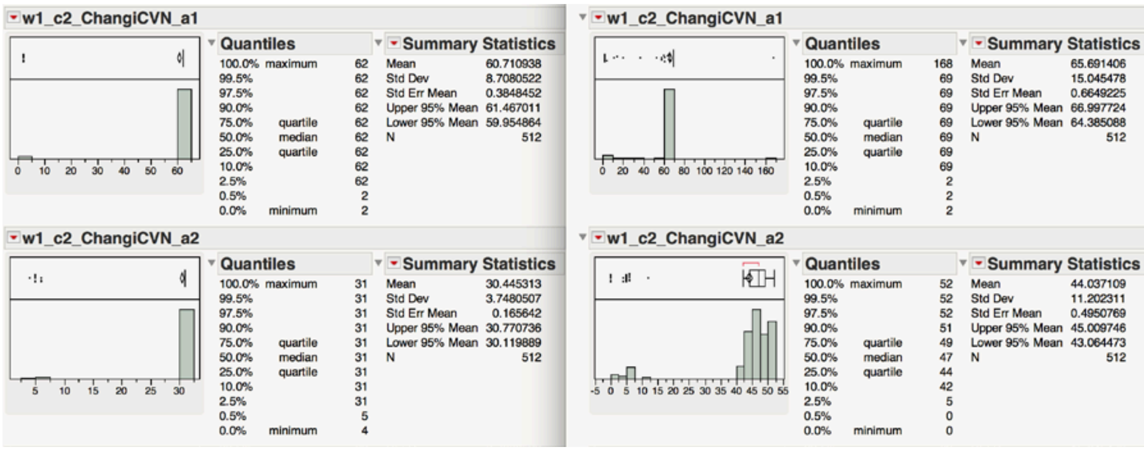


Figure 23. Distribution comparison of C-2 usage in Design 2 (left) versus Design 3 (right).

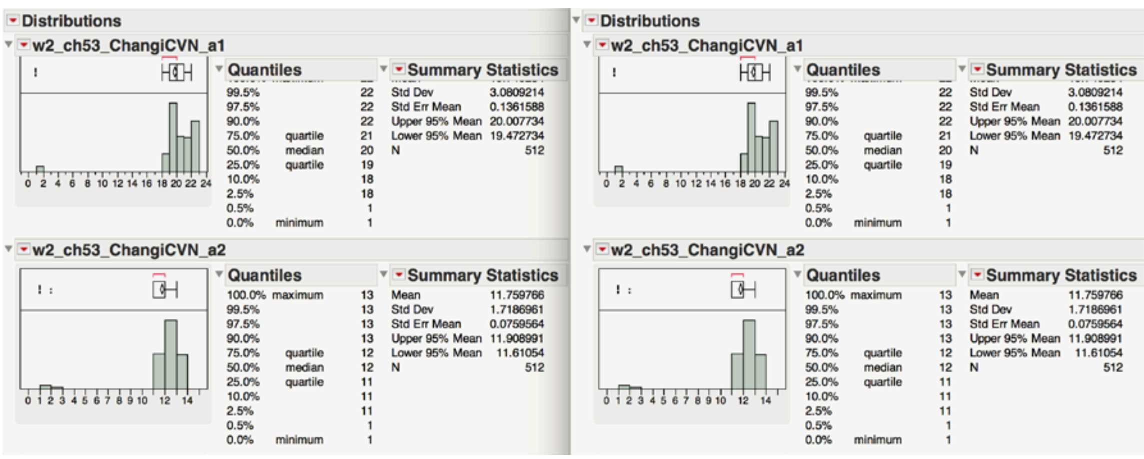


Figure 24. Distribution comparison of CH-53 usage in Design 2 (left) versus Design 3 (right).

4. Final Design

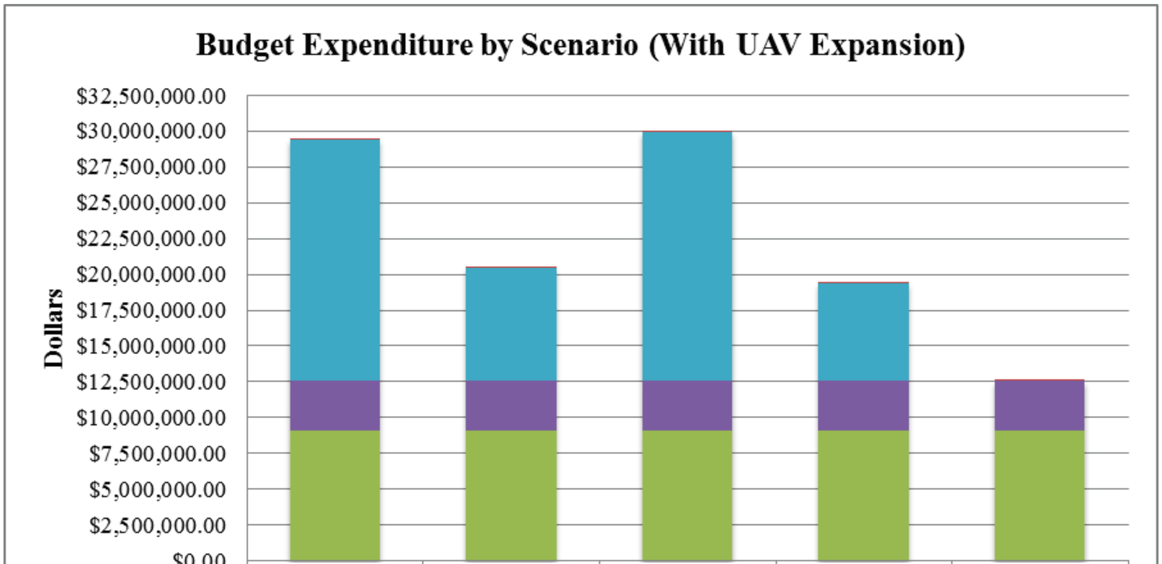
The Final Design contains many of the same factors and factor values as Design 3, but is different in that we change the demand to levels between Design 1 and Design 3 (see Appendix A). The demand reflects the impact of a storm ten times greater than in Design 3 for scenarios ω_1, ω_2, ω_3, **and** ω_4. For scenario ω_5 the demand is zero for commodities and injury transportation. This is so we can see the budgetary impact of making first-stage decisions, even when the predicted storm does not make landfall and there is no demand. Also, this design is run for three budget levels ($30 million, $10 million, and $0) and two different variants of UAV expansion: one where UAVs are able to expand and another where additional UAVs are precluded from playing a role in commodity delivery. Since we observed, in Designs 2 and 3, that in most scenarios the budget is not entirely spent, we want to identify if the objectives and solutions are the same. If it is possible to allocate less toward budget and still meet demand, this will help to answer the question posed early in this thesis of how the military can provide the same quantity of FHA support in the wake of budget cuts.

After running the design on AAM and obtaining the data, we select a design point at random to conduct some more detailed comparative analysis. We first compare the objective values for the six cases of that design point. We discover that when permitted to expand the number of UAVs, the optimal objective value decreases in two of three budget allocation cases. With no budget there is no opportunity to make first or second-stage decisions to expand to meet greater demand, thus limiting the ability to meet demand and increasing the optimal objective values. Table 5 shows the objective value comparison for design point 17. Note that when no UAV expansion is available, the optimal objective value for a $30 million budget equals the optimal objective value for a $10 million budget. Thus, even if an additional $20 million is available, it is of no help if it cannot be used to purchase UAVs. This indicates a shortfall of other (non-UAV(assets available for purchase. In the cases where UAV expansion is permitted, the optimal objective values are lower than for no UAV expansion, the inclusion of UAVs as an available transportation means is beneficial for getting closer to meeting demand.

Table 5. Design point 17 objective value comparison.

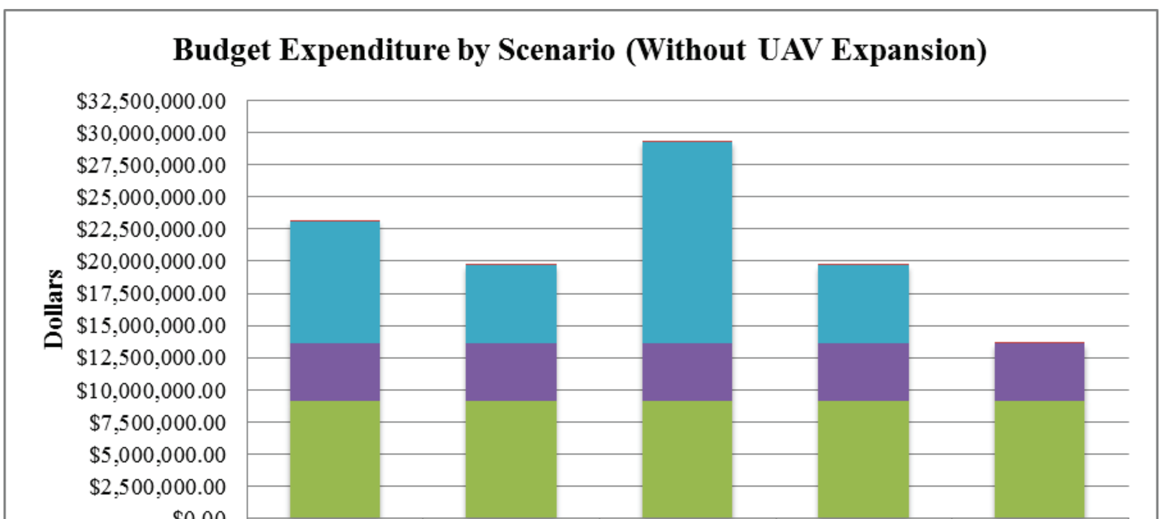
Allocated Budget	With UAV Expansion	No UAV Expansion
$30 million	7,315.77	11,359.79
$10 million	7,687.85	11,359.79
None	13,241.81	13,241.81

Next, we take a closer look at the budget distribution for each of the six cases for design point 17. For a $30 million budget with and without UAV expansion there are differences between spending on first- and second-stage decisions. With UAV expansion we see less spending on first-stage ramp space and more spending on second-stage transportation means, while for no UAV expansion there is more spending on ramp space than transportation means. This trend continues in scenario ω_5, which is when the natural disaster does not happen and there is no demand for injury transport or commodities. The first-stage decisions still have to take place, but for UAV expansion there is less spending on ramp space than for the scenarios without UAV expansion—ultimately reducing the total budget spent to prepare for a storm that does not impact the population. Despite being unable to achieve objective values of zero, in neither case was the entire budget spent, indicating the shortfall is not with budget, but with resources available to expand upon. Figure 25 is the budget breakdown for a $30 million budget with UAV expansion, and Figure 26 is the budget breakdown for a $30 million budget without UAV expansion.



	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Medical	$90,000.00	$90,000.00	$90,000.00	$90,000.00	$90,000.00
Transportation	$16,852,977.82	$7,899,908.35	$17,379,558.38	$6,846,747.23	$0.00
Ramp Space	$3,440,441.62	$3,440,441.62	$3,440,441.62	$3,440,441.62	$3,440,441.62
Commodities	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00

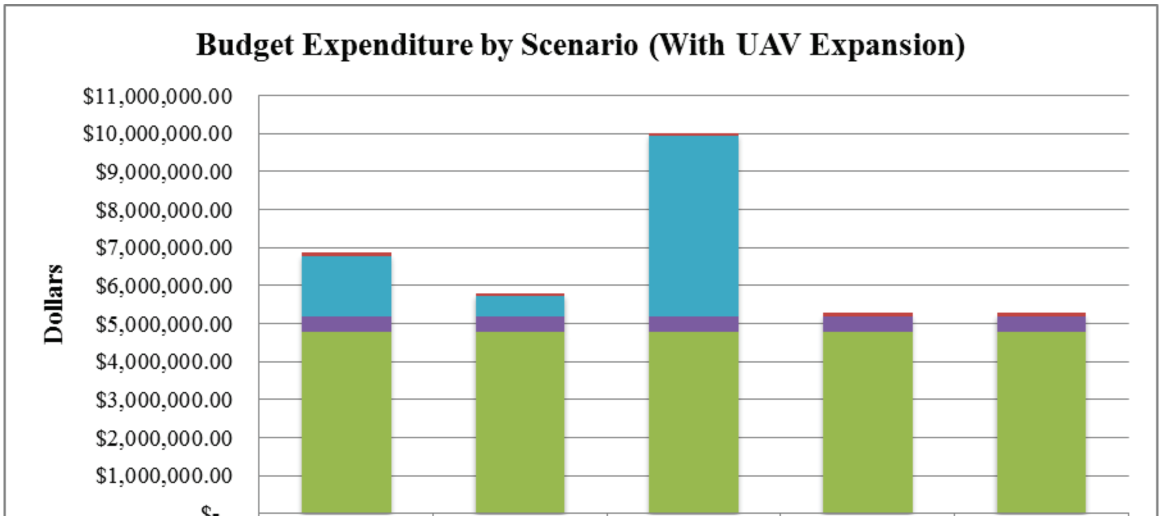
Figure 25. Budget expenditure by scenario for a $30 million budget with UAV expansion capability.



	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Medical	$90,000.00	$90,000.00	$90,000.00	$90,000.00	$90,000.00
Transportation	$9,511,143.74	$6,091,829.10	$15,689,533.92	$6,091,829.10	$0.00
Ramp Space	$4,466,610.18	$4,466,610.18	$4,466,610.18	$4,466,610.18	$4,466,610.18
Commodities	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00

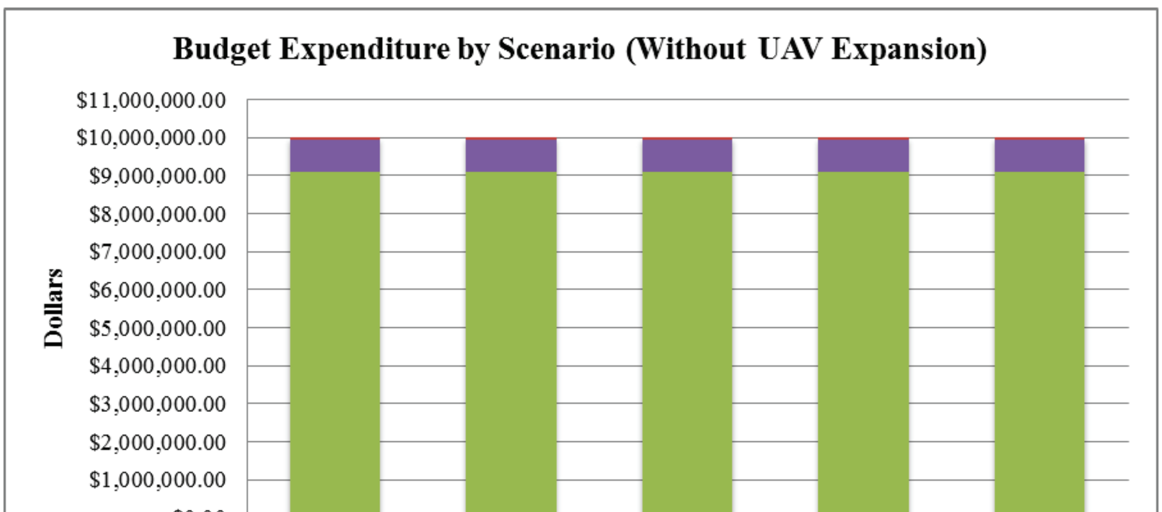
Figure 26. Budget expenditure by scenario for a $30 million budget without UAV expansion capability.

As we observe in Table 5, the demand is not met as indicated by optimal objective values greater than zero for all cases of design point 17. So when the budget expenditure shows that the budget is not completely spent, just as with the $30 million budget, we again look toward the maximum expansion allowed to identify the shortfalls. The observations made with a lower budget of $10 million, with the opportunity for UAV expansion, again show that a significant portion of the budget is spent on expanding the transportation means. In the case where UAV expansion is not available, the entire $10 million budget is spent, with the majority of the expenditure on commodities and none of the expenditure on any transportation means expansion. Figures 27 and 28 display the budget breakdown by scenario to show the difference between each scenario and also between both cases. All input data being exactly the same, other than the opportunity to allow UAVs to participate in the relief effort, we conclude that including UAVs in the humanitarian network saves budget in the short run without reducing the level of humanitarian assistance the Navy provides. Reserving resources for future incidents means that in the long run, including UAVs can result in the ability to save more lives.



	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Medical	$90,000.00	$90,000.00	$90,000.00	$90,000.00	$90,000.00
Transportation	$1,579,741.68	$526,580.56	$4,739,225.04	$-	$-
Ramp Space	$407,751.24	$407,751.24	$407,751.24	$407,751.24	$407,751.24
Commodities	$4,763,023.72	$4,763,023.72	$4,763,023.72	$4,763,023.72	$4,763,023.72

Figure 27. Budget expenditure by scenario for a $10 million budget with UAV expansion capability.



	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Medical	$90,000.00	$90,000.00	$90,000.00	$90,000.00	$90,000.00
Transportation	$0.00	$0.00	$0.00	$0.00	$0.00
Ramp Space	$820,000.00	$820,000.00	$820,000.00	$820,000.00	$820,000.00
Commodities	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00	$9,090,000.00

Figure 28. Budget expenditure by scenario for a $10 million budget without UAV expansion capability.

The cases with no budget with and without UAVs showed us no difference between optimal objective values. This is not unexpected, but we ran the two scenarios for completeness to see if multiple solutions might be produced. The cases with no budget are situations in which no planning or coordination ensued for first-stage decisions and there was no budget to expend when it was discovered the demand required additional resources. While some assistance can be provided with existing aircraft and resources, it is not nearly as much as can be achieved with planning prior to the storm and an allocated budget for expanding capabilities before and immediately after the storm occurs. In our particular scenario, the available aircraft are capable of carrying more commodities and people than can be accommodated by the available ramp space and other expandable assets.

This analysis highlights the need to distinguish between an optimal objective value (Z) and the decision factor settings that lead to this value. Multiple optima appear to be commonplace, even when Z is greater than zero. This means that the first-stage decisions (expansion for medical, commodities, and ramp space) are "feasible" rather than "optimal" with regard to the budget constraint (i.e., the budget constraint is not tight), and there is no incentive for the solver to choose first-stage decisions that reduce this budget. The fact that the expenditures by scenario in Figure 27 range from 20 percent to 40 percent of those in Figure 25, yet arrive at the same optimal objective value, means that it is inappropriate to infer that the first-stage decisions from GAMS are optimal (or even particularly good) alternatives. Further research is needed to determine whether this behavior is present in similar two-stage stochastic optimization models for humanitarian assistance, such as those discussed in II.A. For example, Salmeron & Apte (2010) assess the sensitivity of their solution by incrementally increasing their budget while "enforcing expenditure persistence," which they define as requiring "a minimum expenditure in each category given by the solution for the previous budget level." Our results suggest that this may sometimes be counterproductive.

By looking at the objective value differences and the budget distribution we see there is a benefit to the use of UAVs in the FHA logistics network. The allowance of UAV expansion adds the capability for more resources in the network to meet more

demand as demonstrated by the lower objective values. Also, when the option to expand UAVs is permitted we also observed that for the case where the storm does not hit as anticipated the first-stage decision costs were reduced, preventing the unnecessary expenditure of the budget. With the observations in the Final Design, using UAVs for logistics has the potential to assist with saving lives and saving money.

5. Overview of Designs and Outcomes

Conducting DOE on an optimization model provides insight that is otherwise not observed with a deterministic model. Sensitivity analysis for an optimization model cannot always allow a focused investigation of how specific input data directly affects the output in the way DOE permits. Our series of experiments shows which parameters have more influence over the AAM solution and objective values. Such analysis provides disaster relief planners with some guidance when attempting to understand what will have the biggest impact as relief efforts take place and how trade-offs might influence the outcome of the effort.

Recognizing which parameters are changed shows the link between what is discovered with each design. As seen, Design 1 objective values are all very large due to the possibility of a very high demand for commodities. Design 2 demand variation is not great enough to prevent assets from meeting demand, so it is interesting to see where the budget expenditures are most often occurring to arrive at solutions. It was identified transportation was where the majority of budget spending took place. For Design 3, the additional factors are added to include uncertainty with the times the air assets take to travel, ramp space expansion, and transportation means initial and expansion number of units. The changes to the input values highlight the impact those parameters possibly have on the budget. In the Final Design we increase demand for a stronger storm, and model both the current logistics practice (no UAV expansion) and the possibility for an introduction of UAVs into the logistics network. We compare the objective value (the minimization of a weighted expected value for unmet commodity demand and unmet injury transportation demand) and the budget distribution between the cases and varying budget levels. In the cases where UAV expansion is permitted we notice lower objective

values, indicating more demand is than when UAV expansion is not permitted. We also notice a difference with first- and second-stage decision expenses on the budget and the decreased spending for first-stage decisions with UAV expansion capabilities.

These results show not only the sensitivity AAM has with regard to input data variance, but also how to assist planners as they determine how to address differing situations that are faced when there is so much uncertainty with what will happen before or after a disaster strikes. Rather than making first-stage decisions based on a single run of AAM, planners can increase their confidence in making good choices by focusing on first-stage decisions associated with good outcomes across a wide spectrum of potential futures. As one compelling example, the employment of UAVs is beneficial in all of the designs. Considering the use of UAVs to reduce the workload on manned aircraft in FHA, and possibly in standard naval operations, will only improve naval logistics overall.

V. CONCLUSION AND FUTURE WORK

A. CONCLUSION

The DOD contribution to foreign humanitarian assistance is both strategic and noble, assisting to create a perception of the U.S. military internationally as a force for good. U.S. military capabilities allow for quick deployment of resources and services that are needed immediately following a disaster, reinforcing the value of DOD participation during the emergent phase of a disaster relief effort. However, budget limitations, an increase in the frequency of crises, and growing operational requirements all threaten to prevent the quantity of support that the military can provide.

From this thesis, we can conclude that optimization models do provide some good insights into helping prepare for providing humanitarian assistance operations. As with any model, the results are dependent upon the assumptions that are made and there *are* limitations. The introduction of probabilities for scenarios occurring adds some uncertainty to the model; however, based upon the results of the experimental design, that uncertainty is not enough to fully capture the potential situations that can arise with natural disaster response.

As we explore the impact of the parameters and their assigned levels on the solution, we realized there are changes in the output. For the case with overwhelming demand, the objective values and decision variable solutions display variance, while in the designs with decreased demand, but with an increase in varied parameters, the objective values are more consistent, with the variance observed in decision variable solutions. With the addition of more parameters, AAM provides different output, which indicates the level of sensitivity to those changed parameters. AAM is only as good as the assumptions that are made. The DOE approach is necessary to account for a wider range of possibilities and has the opportunity to provide more realistic results. DOE on AAM permits for specific parameters to change as factors for different levels of interest. This gives us the opportunity to focus on specific parameters, rather than conducting broad sensitivity analysis. While a broad analysis is acceptable in many cases, it is appealing to

gain a deeper understanding of how certain parameters affect the objective specifically when trying to conduct analysis on trade-offs or understanding the relationship between certain parameters and the desired outcome.

Additionally, it was of particular interest to see how valuable UAVs are to the solution. In every case, the model prefers to use UAVs to deliver commodities as ideal solutions. This is most demonstrated with the analysis conducted on the Final Design where we compare the exact same scenarios with two different possibilities of including or not including UAVs in the network. With the use of AAM and DOE it is demonstrated that UAVs as logistic assets have the potential to add much benefit to FHA when saving lives and money.

B. FUTURE WORK

There are numerous opportunities for further research with AAM and the DOE methodology explained in this thesis. AAM has the potential to become more sophisticated by changing the travel pattern of the transportation means, adding more flexibility in the relief locations that the air assets visit, or changing when some expansion decisions are made, such as allowing medical or ramp space decisions to occur in the second-stage versus the first-stage. Furthermore, the decision of which ships respond for the relief effort is hardcoded. Giving AAM the opportunity to make the decision of which ships respond could offer a better solution and give deeper insight into trade off analysis. Alternatively, since Navy vessels are mobile, further experiments could explore the robustness of the first-stage decisions to variations in the set of assets within range of the affected areas when disaster strikes. Further investigation needs to take place to completely understand why some of the experiments resulted in the same objective value for all 512 design points. While it is believed it is due to the potential for multiple optimal solutions and easily met demand, we will not fully realize that unless there is more research on the relationships and sensitivity. Better ways of identifying and dealing with multiple optimal solutions are also needed.

With respect to DOE, there are many possible combinations of experiments to run. First, we should take a closer look at how the variance in the design carries into the

budget or the penalty factor, and then into the objective value, which might help to bring clarity to the variance attributable to certain decision variables. Also, it would be interesting to see when it becomes most beneficial to only use UAVs to deliver commodities or at what demand levels does the objective value just barely creep above zero. Using the large-scale DOE methodology on the POM may also yield some interesting observations to the results that might not have been expected by conducting more limited sensitivity analysis. One benefit of DOE is if a question arises while trying to identify what happens to the output when certain input values are used, then it is possible to run additional experiments to gain deeper understanding.

C. FINAL THOUGHTS

The motivation for this thesis is a desire to assist logistic planners and help the Navy respond to humanitarian assistance requests in a timely and effective manner. This thesis shows the potential in developing quantitative methods that can be applied to assist in this process—ultimately saving lives, recognizing the opportunity for cost savings, and increasing goodwill toward the U.S. military.

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APPENDIX A. FACTORS AND LEVELS FOR DESIGNS

This appendix has two tables. Table 6 contains the initial 15 factors and levels for all three designs, while Table 7 contains the remaining 12 factors and levels for Design 3.

Table 6. First 35 factors and levels used in Designs 1 through Final Design.

Factor	Design 1 Ranges	Design 2 Ranges	Design 3 Ranges	Final Design Ranges
Probability ω_1 (p_{ω_1})	[0, 0.25]	Same as Design 1.	Same as Design 1.	Same as Design 1.
Probability ω_2 (p_{ω_2})	[0, 0.25]	Same as Design 1.	Same as Design 1.	Same as Design 1.
Probability ω_3 (p_{ω_3})	$p_{\omega_3} = \begin{cases} (p_{\omega_1}+p_{\omega_2})/2, \\ 0, \end{cases}$	Same as Design 1.	Same as Design 1.	Same as Design 1.
Probability ω_4(p_{ω_4})	$p_{\omega_4} = \begin{cases} (p_{\omega_1}+p_{\omega_2}+p_{\omega_3}) \end{cases}$	Same as Design 1.	Same as Design 1.	Same as Design 1.
Probability ω_5 (p_{ω_5})	$p_{\omega_5} = 1-(p_{\omega_1}+p_{\omega_2}+$	Same as Design 1.	Same as Design 1.	Same as Design 1.
Demand for injury transport from AA 1 in ω_1	[0, 41]	[14, 18]	Same as Design 2.	[210, 270]
Demand for injury transport from AA 1 in ω_2	[0, 41]	[0, 10]	Same as Design 2.	[0,140]
Demand for injury transport from AA 1 in ω_3	[0, 41]	[0, 10]	Same as Design 2.	[0,130]
Demand for injury transport from AA 1 in ω_4	[0, 41]	[14, 18]	Same as Design 2.	[168, 216]
Demand for injury transport from AA 1 in ω_5	[0, 41]	[0, 10]	Same as Design 2	0
Demand for injury transport from AA 2 in ω_1	[0, 139]	[46, 61]	Same as Design 2.	[709, 913]

Demand for injury transport from AA 2 ω_2	[0, 139]	[0, 34]	Same as Design 2.	[0, 473]
Demand for injury transport from AA 2 in ω_3	[0, 139]	[0, 34]	Same as Design 2.	[0, 440]
Demand for injury transport from AA 2 in ω_4	[0, 139]	[47, 61]	Same as Design 2.	[568, 730]
Demand for injury transport from AA 2 in ω_5	[0, 139]	[0, 34]	Same as Design 2.	0
Demand for injury transport from AA 3 in ω_1	[0, 139]	[159, 206]	Same as Design 2.	[1685, 2173]
Demand for injury transport from AA 3 in ω_2	[0,139]	[0, 115]	Same as Design 2.	[0, 1126]
Demand for injury transport from AA 3 in ω_3	[0, 139]	[0, 115]	Same as Design 2.	[0, 1047]
Demand for injury transport from AA 3 ω_4	[0, 139]	[159, 206]	Same as Design 2.	[1352, 1737]
Demand for injury transport from AA 3 ω_5	[0, 139]	[0, 115]	Same as Design 2.	0
Demand for commodities in AA 1 in ω_1	[0, 139]	[46, 56]	Same as Design 2.	[50, 500]
Demand for commodities in AA1 in ω_2	[0, 9000]	[23, 29]	Same as Design 2.	[20, 200]
Demand for commodities in AA 1 in ω_3	[0, 9000]	[92, 112]	Same as Design 2.	[100, 1000]
Demand for commodities in AA 1 in ω_4	[0, 9000]	[23, 29]	Same as Design 2.	[25, 250]
Demand for commodities in AA 1 in ω_5	[0, 9000]	[0, 10]	Same as Design 2.	0
Demand for commodities in	[0, 5310]	[27.14, 33.04]	Same as Design 2.	[29.5, 295]

AA 2 in ω_1				
Demand for commodities in AA 2 in ω_2	[0, 5310]	[13.57, 17.11]	Same as Design 2.	[11.8, 118]
Demand for commodities in AA 2 in ω_3	[0, 5310]	[54.28, 66.08]	Same as Design 2.	[59, 590]
Demand for commodities in AA 2 in ω_4	[0, 5310]	[13.57, 17.11]	Same as Design 2.	[14.75, 147.5]
Demand for commodities in AA 2 in ω_5	[0, 5310]	[0, 5.9]	Same as Design 2.	0
Demand for commodities in AA 3 in ω_1	[0, 1890]	[9.66, 11.76]	Same as Design 2.	[6.2, 62]
Demand for commodities in AA 3 in ω_2	[0, 1890]	[4.83, 6.09]	Same as Design 2.	[2.5, 24.8]]
Demand for commodities in AA 3 in ω_3	[0, 1890]	[19.32, 23.52]	Same as Design 2	[12.4, 123.9]
Demand for commodities in AA 3 ω_4	[0, 1890]	[4.83, 6.09]	Same as Design 2.	[3.1, 30.9]
Demand for commodities in AA 3 in ω_5	[0, 1890]	[0, 2.1]	Same as Design 2.	0

Table 7. The 25 additional factors and levels used in Design Final Design.

Factor	Design 3 Ranges	Final Design Ranges
Multiplier for transportation means travel times	[1.0, 1.5]	Same as Design 3.
Load and unload half-width time	[0.1, 0.5]	Same as Design 3.
AA 1 Initial Ramp Space	[10, 500]	Same as Design 3.
AA 1 Ramp Space Expansion	[10, 100]	Same as Design 3.
AA 1 Ramp Space Expansion Cost	[10000, 100000]	Same as Design 3.
AA 2 Initial Ramp Space	[9, 450]	Same as Design 3.
AA 2 Ramp Space Expansion	[9, 90]	Same as Design 3.
AA 2 Ramp Space Expansion Cost	[9000, 90000]	Same as Design 3.
AA 3 Initial Ramp Space	[8.1, 405]	Same as Design 3.
AA 3 Ramp Space Expansion	[8.1, 81]	Same as Design 3.
AA 3 Ramp Space Expansion Cost	[8100, 81000]	Same as Design 3.
MV-22 Initial Units	[2, 8]	Same as Design 3.
MV-22 Expansion Units	[0, 10 - initial units]	Same as Design 3.
CH-53 Initial Units	[1, 6]	Same as Design 3.
CH-53 Expansion Units	[0, 12 - initial units]	Same as Design 3.
UH-1 Initial Units	[1, 5]	Same as Design 3.
UH-1 Expansion Units	[0, 9 - initial units]	Same as Design 3.
C-2 Initial Units	[1, 3]	Same as Design 3.
C-2 Expansion Units	[0, 3 - initial units]	Same as Design 3.
SH-60 Initial Units	[4, 16]	Same as Design 3.
SH-60 Expansion Units	[0, 36 - initial units]	Same as Design 3.
ARES Initial Units	[5, 20]	0
ARES Expansion Units	[0, 20 - initial units]	0 or [5, 20]
MQ-8 Initial Units	[1, 6]	2
MQ-8 Expansion Units	[0, 6 - initial units]	0 or [2,7]

APPENDIX B. RUBY SCRIPT TO PULL DESIGN INTO GAMS

This appendix shows the Ruby script that was used to pull the CSV design files into the AAM. Specifically, the probabilities and demand data was changed with this script, which was developed with the help of Dr. Paul Sanchez.

```
#!/usr/bin/env ruby -w
if ARGV.length < 2
  STDERR.puts "Must supply name of design file and
  template file on command-line"
  exit 1
end
design_filename = ARGV.shift
template_filename = ARGV.shift
output_filename = (ARGV.shift || "dp")
design_points = IO.readlines(design_filename)
original_template_data                                    =
IO.readlines(template_filename)
design_points.each.with_index do |dp, i|
  current_output_filename = output_filename + ("_%05d"
% (i+1)) + ".gms"
  outfile = File.open(current_output_filename, "w")
  template_data = original_template_data.clone
  input_data = dp.strip.split(",")
  while line = template_data.shift do
    if line =~ /TABLE data_w\(w,\*\)/
      outfile.puts line
      while line = template_data.shift do
        if line =~ /\sp_w$/
          outfile.puts line
          break
        end
        outfile.puts line
      end
      while line = template_data.shift do
        if line =~ /;/
          outfile.puts line
          break
        end
        data = line.split(/\s+/)
        data[2] = input_data.shift
        outfile.puts data.join("\t")
      end
    elsif line =~ /TABLE dsur_w\(a,w\)/
```

```
  outfile.puts line
  while line = template_data.shift do
    if line =~ /\sw5$/
      outfile.puts line
      break
    end
    outfile.puts line
  end
  while line = template_data.shift do
    if line =~ /;/
      outfile.puts line
      break
    end
    data = line.split(/\s+/)
    data[1] = input_data.shift
    data[2] = input_data.shift
    data[3] = input_data.shift
    data[4] = input_data.shift
    data[5] = input_data.shift
    outfile.puts data.join("\t")
  end
elsif line =~ /TABLE dcom_w\(a,w\)/
  outfile.puts line
  while line = template_data.shift do
    if line =~ /\sw5$/
      outfile.puts line
      break
    end
    outfile.puts line
  end
  while line = template_data.shift do
    if line =~ /;/
      outfile.puts line
      break
    end
    data = line.split(/\s+/)
    data[1] = input_data.shift
    data[2] = input_data.shift
    data[3] = input_data.shift
    data[4] = input_data.shift
    data[5] = input_data.shift
    outfile.puts data.join("\t")
  end
else
  outfile.puts line
end
```

```
  end
  outfile.close
end
```

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APPENDIX C. EXAMPLE OF RUBY SCRIPT USED FOR DESIGN 3

This Ruby script was used for the third design to make changes to probabilities, demand, times, ramp space data, and transportation means data. This script was developed with the assistance of Dr. Susan Sanchez.

```
#!/usr/bin/env ruby -w

if ARGV.length < 2
  STDERR.puts "Must supply name of design file and
template file on command-            line"
  exit 1
end
design_filename = ARGV.shift
template_filename = ARGV.shift
output_filename = (ARGV.shift || "dp")
design_points = IO.readlines(design_filename)
original_template_data                                  =
IO.readlines(template_filename)
design_points.each.with_index do |dp, i|
  current_output_filename = output_filename + ("_%05d"
% (i+1)) + ".gms"
  outfile = File.open(current_output_filename, "w")
  template_data = original_template_data.clone
  input_data = dp.strip.split(",")
  while line = template_data.shift do
    if line =~ /TABLE data_w\(w,\*\)/
      outfile.puts line
      while line = template_data.shift do
        if line =~ /\sp_w$/
          outfile.puts line
          break
        end
        outfile.puts line
      end
      while line = template_data.shift do
        if line =~ /;/
          outfile.puts line
          break
        end
        data = line.split(/\s+/)
        data[2] = input_data.shift
        outfile.puts data.join("\t")
```

```
    end
  elsif line =~ /TABLE dsur_w\(a,w\)/
    outfile.puts line
    while line = template_data.shift do
      if line =~ /\sw5$/
        outfile.puts line
        break
      end
      outfile.puts line
    end
    while line = template_data.shift do
      if line =~ /;/
        outfile.puts line
        break
      end
      data = line.split(/\s+/)
      data[1] = input_data.shift
      data[2] = input_data.shift
      data[3] = input_data.shift
      data[4] = input_data.shift
      data[5] = input_data.shift
      outfile.puts data.join("\t")
    end
  elsif line =~ /TABLE dcom_w\(a,w\)/
    outfile.puts line
    while line = template_data.shift do
      if line =~ /\sw5$/
        outfile.puts line
        break
      end
      outfile.puts line
    end
    while line = template_data.shift do
      if line =~ /;/
        outfile.puts line
        break
      end
      data = line.split(/\s+/)
      data[1] = input_data.shift
      data[2] = input_data.shift
      data[3] = input_data.shift
      data[4] = input_data.shift
      data[5] = input_data.shift
      outfile.puts data.join("\t")
    end
  elsif line =~ /TABLE transport_time\(t,j,a,w\)/
```

```
    outfile.puts line
    while line = template_data.shift do
      if line =~ /\sa3.w5$/
        outfile.puts line
        break
      end
      outfile.puts line
    end
    multiplier = input_data.shift.to_f
    width = input_data.shift.to_f
    while line = template_data.shift do
      if line =~ /;/
        outfile.puts line
        break
      end
      data = line.split(/\s+/)
      outfile.print(data[0])
      15.times do |j|
        data[j+1] = data[j+1].to_f * multiplier +
        (rand-0.5)*width
        outfile.print "\t" + '%.2f' % data[j+1]
      end
      outfile.print("\n")
    end
  elsif line =~ /TABLE affecteddata\(a,\*\)/
    outfile.puts line
    while line = template_data.shift do
      if line =~ /\svecr$/
        outfile.puts line
        break
      end
      outfile.puts line
    end
    while line = template_data.shift do
      if line =~ /;/
        outfile.puts line
        break
      end
      data = line.split(/\s+/)
      data[1] = input_data.shift
      data[2] = input_data.shift
      data[3] = input_data.shift
      outfile.puts data.join("\t")
    end
  elsif line =~ /TABLE transportdata\(t,\*\)/
    outfile.puts line
```

```
      while line = template_data.shift do
        if line =~ /\sr$/
          outfile.puts line
          break
        end
        outfile.puts line
      end
      while line = template_data.shift do
        if line =~ /;/
          outfile.puts line
          break
        end
        data = line.split(/\s+/)
        data[1] = input_data.shift
        data[2] = input_data.shift
        outfile.puts data.join("\t")
      end
    else
      outfile.puts line
    end
  end
  outfile.close
end
```

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